Earnings or cash flows: Which is a better predictor of future cash flows?

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> > August 10, 2018

We thank Sanjeev Bhojraj, Brian Bratten, David Burgstahler, Qi Chen, Shane Dikolli, Scott Dyreng, Peter Easton, Robert Hills, Paul Hribar, Xu Jiang, Matthew Kubic, Alina Lerman (Discussant), Robert Libby, Bill Mayew, Linda Myers, Maria Ogneva (Discussant), Srini Rangan (Discussant), Robert Resutek, Katherine Schipper, Lakshmanan Shivakumar, Theodore Sougiannis, Karen Ton, Rahul Vashishtha, Stephen Zeff and workshop participants at Boston University, Duke University, Rensselaer Polytechnic Institute, Rice University, University of Kentucky, and participants at the Cornell Accounting Summer Mini-Conference (2018), Harvard Business School IMO Conference (2018), Financial Accounting and Reporting Section Midyear Meeting (2018), Southeast Summer Accounting Research Conference (2017), UIC Accounting Conference (2017), Indian School of Business Accounting Research Conference (2017), and Carnegie Mellon University Accounting Symposium (2017). A previous version of this manuscript was titled "The changing landscape of accrual accounting: Implications for operating cash flow predictability." Any remaining errors are our own.

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Abstract

We reexamine the relative ability of earnings and cash flows in predicting future cash flows to achieve two objectives: (i) reconcile the mixed evidence in the prior literature, and (ii) investigate the implications of temporal shifts in accrual accounting for trends in cash flow predictability. Three key insights emerge from our analyses. First, contrary to conventional wisdom, we find that cash flows are superior to earnings in predicting future cash flows. After evaluating several alternative explanations, we attribute the mixed evidence in prior research mainly to measurement errors induced by the balance sheet method of estimating cash flows. Second, we find that earnings' ability to predict future cash flows is increasing over the period 1989-2015. However, this trend is attributable to the increasing predictive ability of cash flows rather than accruals. That is, while cash flows show an increasing ability to predict future cash flows is associated with shortening operating cycles, decreasing working capital accruals, and increasing intensity of intangibles over time.

Earnings or cash flows: Which is a better predictor of future cash flows? 1. Introduction

An extensive literature investigating the relative ability of earnings and cash flows for predicting future cash flows finds mixed evidence.¹ Despite the conflicting evidence, accounting educators, regulators, standard setters, and scholars continue to extol earnings as a superior summary measure for predicting future cash flows (e.g., Dechow, Kothari, and Watts 1998; Kim and Kross 2005; Barth, Clinch, and Israeli 2016; Revsine, Collins, Johnson, Mittelstaedt, and Soffer 2018). The primary objective of this study is to revisit and reexamine the predictive ability of earnings and cash flows for future cash flows to help reconcile the contradictory evidence in the literature.

Notwithstanding the mixed evidence in prior literature, temporal shifts in the accounting landscape underscore the importance of reexamining the predictive ability of earnings for future cash flows. In particular, Bushman, Lerman, and Zhang (2016) document that the negative contemporaneous correlation between accruals and cash flows has been declining over time and has largely disappeared in recent years. Bushman et al. (2016) point out that the decline in negative correlation is primarily due to the increase in the incidence of one-time and non-operating items in earnings over time. While one-time items may diminish the predictive ability of accruals and cash flows signals the presence of orthogonal information content in these two components of earnings that when aggregated help predict future cash flows better. In addition, Lev, Li, and

¹ While some studies document that cash flows are better than earnings in predicting future cash flows (e.g., Bowen, Burgstahler, and Daley 1986; Finger 1994; Burgstahler, Jiambalvo, and Pyo 1998), other studies find the exact opposite (e.g., Greenberg, Johnson, and Ramesh 1986; Lorek and Willinger 1996; Dechow et al. 1998; Kim and Kross 2005).

Sougiannis (2010) report a positive trend in the prevalence of managerial estimates embedded in accruals particularly due to the move towards fair-value accounting. Whether managerial estimates enhance the quality of earnings by incorporating forward-looking information or diminish earnings quality due to difficulties in estimation and accrual manipulations can differentially affect the predictive ability of earnings for future cash flows.² Therefore, as a secondary objective of this study, we investigate time trends in the relative predictive ability of earnings and cash flows.

To reconcile the contrasting results documented in prior studies on the predictive ability of earnings and cash flows, we identify several possible explanations: (i) measurement approach (measures based on cash flow statement versus balance sheet), (ii) sample period selection and composition, (iii) variable definitions, and (iv) estimation methods (e.g., cross-sectional vs. firm-specific estimation). We begin our empirical analysis using Compustat annual data spanning the period 1989-2015 and then introduce variations in one or more of the above factors to understand their impact on inferences.³ As a starting point, we follow the cash flow statement based approach and measure operating cash flows directly from the cash flow statement, and accruals as earnings before extraordinary items and discontinued operations minus operating cash flows. We use cross-sectional estimations for each sample year to assess the cash flow predictive ability of earnings, cash flows, accruals, and accrual components.

We find that current cash flows are superior to earnings in predicting future cash flows over the entire sample period. More importantly, in every year of the sample period 1989-2015,

² A parallel stream of value-relevance literature examines the trends in earnings informativeness using returns as the dependent variable. This literature documents that the value-relevance of earnings has been steadily declining for equity markets (Collins, Maydew, and Weiss 1997) while simultaneously improving for debt markets (Givoly, Hayn, and Katz 2017). The differential temporal shifts in earnings' informativeness for equity and debt markets is potentially indicative of time-series trends in earnings attributes. However, it is not clear ex ante how, if at all, such changes affect the ability of accruals and earnings to predict future cash flows.

³ Our sample starts from 1989 as SFAS 95 required firms to present a statement of cash flows for fiscal years ending after July 15, 1988. Using a cash flow statement based approach for measuring cash flows and accruals requires the availability of a cash flow statement corresponding to the firm-year observation.

cash flows are superior to earnings. On average, cash flows' predictive ability is about 1.5 times that of earnings. Our finding that cash flows are superior to earnings is consistent with one stream of prior literature (e.g., Bowen et al. 1986; Finger 1994; Burgstahler et al. 1998), but inconsistent with the other stream (e.g., Greenberg et al. 1986; Lorek and Willinger 1996; Dechow et al. 1998; Kim and Kross 2005).

We first explore differences in measurement approach as a plausible explanation for the contrasting findings in the literature. While some studies follow a balance sheet based approach for measuring cash flows (e.g., Dechow et al. 1998; Kim and Kross 2005), other studies adopt a more direct cash flow statement based approach (e.g., Barth, Cram, and Nelson 2001; Lev et al. 2010). Hribar and Collins (2002) document that measurement errors associated with computing accruals and cash flows using the balance sheet approach can affect inferences. To explore this explanation, we re-estimate the models after constructing cash flows using a balance sheet approach but using the same sample and research design. Our results are strikingly different when we adopt a balance sheet approach in measuring cash flows; we now find that earnings display greater predictive ability than cash flows, i.e. exactly the *opposite* of our finding above. This evidence suggests that the contrasting conclusions in the prior literature are likely an artifact of the measurement approach used for estimating cash flows.⁴ We continue to explore other explanations such as alternative variable definitions (earnings, cash flows, accruals), estimation methods (crosssectional versus firm-specific time-series prediction models), and sample composition (large firms, small firms, constant sample). However, none of our inferences are sensitive to these alternative

⁴ We repeat our estimation using the balance-sheet approach after eliminating the firm-year observations most impacted by measurement errors, such as those corresponding to M&A deals, divestitures, and foreign currency translations (Hribar and Collins 2002). Despite such sample adjustments to reduce measurement error when using the balance sheet approach, earnings outperform cash flows in predicting future cash flows. These findings suggest that such adjustments do not eliminate accrual estimation errors stemming from a balance-sheet approach (Hribar and Collins 2002).

explanations. Our results are also robust to out-of-sample tests. Thus, we conclude that the main driver of the contradictory findings in prior literature is differences in the measurement approach adopted for estimating cash flows.

Having reconciled the contrasting results in prior literature, we next explore time-series trends in the predictive ability of earnings and cash flows. Our findings indicate that earnings' ability to predict future cash flows is increasing over time – i.e., the explanatory power, as measured by Adj. R^2 , increases from 14 percent in 1989 to 37 percent in 2015. On average, the explanatory power of earnings increases by 0.96 percent per year, and this increasing trend is significant at the 1 percent level. Interestingly, cash flows' ability to predict future cash flows is also increasing over time with an identical increase in explanatory power.

This begs the question of whether and how much accruals play a role in explaining the trend observed in earnings' ability to predict future cash flows. To explore this, we estimate the incremental predictive ability of individual earnings components (i.e., accruals and cash flows). We find that the *incremental* explanatory power of accruals in predicting future cash flows is marginal, ranging from 1 percent to 3 percent during our sample period, and it does not exhibit any time trend. In contrast, cash flows' *incremental* predictive ability increases from 22 percent in 1989 to 53 percent in 2015, trending at 1.2 percent per year. This finding implies that the observed trend in earnings' predictive ability is mostly attributable to cash flows, with accruals contributing very little.

Accruals in aggregate contribute only marginally to predictive ability of earnings for future cash flows, but does disaggregating accruals into components help? When we disaggregate accruals into its components following Barth et al. (2001), the incremental predictive ability of accrual components ranges from 2 percent to 8 percent but exhibits no time trends. Furthermore, we also decompose total accruals based on managerial estimates embedded in accruals (Lev et al. 2010). We fail to find any trends in accrual components with or without significant managerial estimates. Together, these results imply that the changing properties of accruals over time have little effect on the increasing trend in earnings' predictive ability.

While our results thus far indicate that the increasing predictive ability of earnings for future cash flows is primarily due to cash flows, it is not obvious what factors explain the increasing trend in the explanatory power of cash flows. We consider several factors: firms' operating cash cycles, magnitude of working capital, and intangible intensity (see Dechow et al. 1998; Bushman et al. 2016). We find that decreasing operating cycle, decreasing working capital, and increasing intangible intensity over time are partly responsible for the increasing predictive ability of cash flows for future cash flows, with declining operating cycle being the most dominant driver.

If declining operating cycles contribute to the increasing predictive ability of cash flows, we conjecture that the relative superiority of cash flows over earnings in predicting future cash flows should diminish with shorter forecast horizon (e.g., quarterly and semi-annual frequency). Therefore, we consider an alternative prediction model in which we use quarterly and semi-annual measures instead of annual measures. Consistent with expectations, we find that the predictive ability of earnings is on average *better* than that of cash flows at shorter frequencies. This finding not only provides additional evidence that shortening operating cycles drive superior cash flows' predictive ability at annual horizons but also helps reconcile the contrasting findings in prior research that use data based on different frequencies (e.g., Lorek and Willinger 1996; Nam, Brochet, and Ronen 2012). However, it is important to note that most practical applications (e.g.,

equity valuation and credit analysis) require prediction at the annual frequency rather than on a quarterly basis.

Finally, we explore whether our main findings in this study are peculiar to the US or generalizable to international settings. Similar to the evidence from the US sample, the evidence from the international sample suggests that cash flows are superior to earnings in predicting future cash flows. Also, we find that the predictive ability of both earnings and cash flows is increasing over time for the international sample, and that the increase in earnings' predictive ability is almost entirely attributable to the cash flows component. Overall, international sample firms exhibit a trend similar to that of US firms, consistent with our conjecture that economic forces rather than reporting standards are responsible for the observed phenomena.

Our study has implications for accounting educators, academics, practitioners, and policy setters. The importance of cash flows, relative to accruals and earnings, in predicting future cash flows is relevant for practitioners and educators who commonly promote and use earnings as the summary metric for cash flow prediction purposes. The Financial Accounting Standards Board (FASB), in its conceptual framework, asserts that a primary objective of financial reporting is to help existing and potential investors, lenders, and other stakeholders assess the amount, timing, and uncertainty of future expected cash flows (FASB 1978, 2010). The conceptual framework further outlines that earnings provide a better basis than current cash flows for assessing a firm's future expected cash flows. Accounting standard setters such as the FASB and the IASB would find our evidence relevant as it challenges one of the important tenets of financial reporting, i.e., that accounting earnings provide a better basis for predicting future cash flows because of the accrual basis of accounting. Our paper adds to the evidence in Bushman et al. (2016) by documenting that although the landscape of accrual accounting has changed, this per se does not

affect the predictive ability of earnings for future cash flows. Most importantly, our paper helps reconcile conflicting results in the prior literature on the relative ability of earnings and cash flows to predict future cash flows.

2. Related Literature

In this section, we review studies that are pertinent to the twin objectives of our paper: (i) determining the relative predictive ability of earnings and cash flows, and (ii) examining timeseries trends in the predictive ability. An extensive literature, spanning about four decades, investigates the relative ability of earnings and cash flows to predict future cash flows (refer to Table 1 for a detailed summary). Overall, the evidence on the relative predictive ability of earnings and cash flows is mixed, with an even split as to which measure is superior. In particular, several studies (e.g., Brooks 1982; Greenberg et al. 1986; Lorek and Willinger 1996; Dechow et al. 1998; Kim and Kross 2005; Nam et al. 2012) document that earnings are better than current cash flows in predicting future cash flows, while other studies (e.g., Bowen et al. 1986; Finger 1994; Burgstahler et al. 1998; Subramanyam and Venkatachalam 2007; Lorek and Willinger 2009; Chen et al. 2017) document the opposite. The apparent contradiction is likely due to differences in measurement approaches, variable definitions, sample selection, and other research design choices. For example, some studies employ the balance sheet method to estimate cash flows (e.g., Dechow et al. 1998; Kim and Kross 2005), whereas others use more direct measures from cash flow statements (e.g., Burgstahler et al. 1998). Also, while some studies use cross-sectional regression estimation (e.g., Kim and Kross 2005), others employ a firm-specific time-series estimation (e.g., Lorek and Willinger 2009).

Although most studies focus on aggregate earnings and cash flows, some studies disaggregate accruals into its components when evaluating the ability of earnings to predict future

cash flows. Specifically, Barth, Cram, and Nelson (2001) decompose accruals into six major components and document the incremental predictive ability of these components over cash flows to predict future cash flows. Lev, Li, and Sougiannis (2010) decompose accruals into components based on the extent of managerial estimation embedded in accrual components and find that accrual components with substantial estimations do not help predict future cash flows. More recently, Barth, Clinch, and Israeli (2016) find that further partitioning of accruals based on their role in cash flow alignment improves cash flow predictability.

Because earnings' superior ability to predict future cash flows is attributable to accruals, any systematic change in the properties of accruals could alter the predictive ability of earnings and its components. A recent strand of literature suggests several temporal changes in accrual properties. For example, a well-accepted artifact of accrual accounting is that accruals and cash flows are negatively correlated (Dechow 1994). However, Bushman et al. (2016) document a paradigm shift in this relationship. More specifically, the negative contemporaneous correlation between cash flows and accruals is declining over time, and this relation even turns positive in recent periods. Further, Lev, Li, and Sougiannis (2010) document that managerial estimates are increasing in accruals partly due to the move towards fair-value accounting. Because of these trends, it is important to investigate whether changes in the landscape of accrual accounting affect the ability of earnings and the components of earnings to predict future cash flows over time.

In terms of time trends in the relative predictive ability of earnings and cash flows, Kim and Kross (2005) find that earnings' ability to predict future cash flows is increasing over time. In contrast, Lorek and Willinger (2009) find no trend in either earnings' or cash flows' ability to predict future cash flows. Furthermore, while many studies rely on sample periods that end in the mid-2000s, Bushman et al. (2016) document that the correlation between accruals and cash flows has turned from negative to positive over the last decade.

Our paper is also related to the literature that examines time-series patterns in accounting attributes (e.g., Givoly and Hayn 2000; Dichev and Tang 2008; Srivastava 2014). Over time, accounting matching has become worse (Dichev and Tang 2008) and accounting conservatism has been steadily increasing (Givoly and Hayn 2000). Such trends could potentially affect the properties of earnings in terms of cash flow predictability. Furthermore, successive cohorts of newly listed firms have more revenues, higher cash flow volatility, and lower matching between revenues and expenses, and including these firms in the sample affects earnings attributes (Srivastava 2014). Given the fundamental importance of reliably predicting future cash flows, the mixed findings from prior research, and the temporal shifts in the landscape of accrual accounting over time, we believe it is important to re-examine the predictive ability of earnings and cash flows to reconcile the contrasting findings in the literature and investigate the trends in their relative predictive ability.

3. Data, Variable Measurement, and Descriptive Statistics

We obtain all financial statement data from Compustat for the period 1989-2015. Our sample starts from 1989 as SFAS 95 required firms to present a statement of cash flows for fiscal years ending after July 15, 1988. We exclude financial services firms (SIC codes 6000-6999) and observations with either sales of less than \$10M or share price of less than \$1. Our sample selection criteria yield a final sample of 118,624 firm-year observations for our main specifications. We winsorize all continuous independent variables at the 1 percent and 99 percent levels to mitigate the effects of outliers.

Following prior literature (e.g., Barth et al. 2001; Bushman et al. 2016), we define earnings (EARN) as income before extraordinary items and discontinued operations. Cash flows (CF) are measured as cash flows from operations adjusted for extraordinary items and discontinued operations (derived from cash flow statements). Accruals (ACC) are computed as the difference between EARN and CF. Accrual components are taken from the statement of cash flows and, where missing, assigned a value of zero. We scale all variables by average total assets. Table 2 provides descriptions and measurement details for all variables.

Table 3 presents descriptive statistics. Consistent with prior literature (Barth et al. 2001), the means and medians for earnings and cash flows are positive, while those for accruals are negative. We note that the standard deviations of accruals (0.106) and cash flows (0.115) are comparable to and lower than that of earnings (0.135). Current accruals (change in accounts receivable (CHG_AR), change in inventory (CHG_INV), and change in accounts payable (CHG_AP) are much smaller in magnitude than depreciation expense (DEPR). Amortization expense (AMORT) is zero for almost half the sample. Overall, all our descriptive statistics are comparable to those reported in prior research.

Table 4 presents the correlation coefficients of the key variables. As expected, cash flows and accruals are significantly positively correlated with earnings. Specifically, the Pearson correlation coefficient between cash flows (accruals) and earnings is 0.632 (0.554) and is statistically significant at the 1 percent level. For the full sample, we find that cash flows and accruals are negatively correlated. Specifically, the Pearson (Spearman) correlation between accruals and cash flows is -0.269 (-0.398) and is statistically significant. Note that the full sample correlations mask the time-series pattern in the correlation structure documented in Bushman et

al. (2016). Overall, correlations among variables in our sample are as expected and in line with prior research.

4. Empirical Results

4.1 Cash flow predictability: Relative ability of earnings and cash flows

In this section, we first examine separately the ability of earnings and cash flows to predict future cash flows. We then reconcile the conflicting findings from the prior literature.

To investigate the predictive ability of earnings for future cash flows, we estimate the following model by year:

$$CF_{i,t} = \beta_0 + \beta^{\text{EARN}} EARN_{i,t-1} + \varepsilon_{i,t}$$
⁽¹⁾

where CF is net cash flow from operating activities less cash flow from extraordinary items and discontinued operations (estimated from the cash flow statement); EARN is income before extraordinary items and discontinued operations; and *i* and *t* are subscripts to denote firm and year, respectively.⁵ Next, to investigate the ability of current cash flows to predict future cash flows, we estimate the following model by year:

$$CF_{i,t} = \beta_0 + \beta^{CF} CF_{i,t-1} + \varepsilon_{i,t}$$
⁽²⁾

Results presented in Panel A of Table 5 indicate that the predictive ability of cash flows for future cash flows is significantly higher than the predictive ability of earnings for future cash flows (see columns (2) and (4) of Table 5, Panel A). In particular, the explanatory power of cash flows is 1.5 times that of earnings on average, and cash flows perform better than earnings in every sample year. This finding is in sharp contrast to FASB assertions and recent evidence supporting the superiority of earnings as a summary metric for predicting future cash flows.

⁵ We consider several alternative definitions of earnings and cash flows later.

To reconcile the contrasting evidence in prior literature, we explore several possible explanations. Specifically, we consider alternative (i) approaches for measuring accruals and cash flows (i.e., the cash flow statement approach versus the balance sheet approach), (ii) variable definitions (i.e., for earnings, cash flows, and accruals), (iii) estimation methods (e.g., cross-sectional vs. firm-specific time-series prediction models), and (iv) sample selection (e.g., large vs. small firms).

4.1.1 Balance sheet vs. cash flow approach to measuring cash flows

Many prior studies use the balance sheet approach to estimate accruals and cash flows rather than the cash flow statement based approach (e.g., Dechow et al. 1998; Kim and Kross 2005). Hribar and Collins (2002) note that such balance sheet based cash flows suffer from measurement errors, especially for firms with mergers and acquisitions activity or discontinued operations, and they advocate the use of the cash flow statement approach to avoid erroneous inferences. Therefore, measurement error in cash flows and accruals variables could drive the differences in findings among various studies.

To ascertain whether differences in measurement approach help reconcile the disparate findings in prior research, we repeat our main empirical tests by estimating cash flows using a balance sheet approach and document the results in Panel B of Table 5.⁶ In sharp contrast to the results obtained using the cash flow statement approach (see Panel A of Table 5), we find that the predictive ability of earnings exceeds that of cash flows in every sample year. This result suggests that the contrasting findings documented by prior literature are an artifact of measurement error introduced by using the balance sheet method of estimating accruals.

⁶ Following Bushman et al. (2016), we measure total accruals as (Changes in non-cash current assets – Changes in non-debt current liabilities – Depreciation Expense) / Total Assets. We then compute cash flows as the difference between earnings and total accruals. See Table 2 for details on computing accruals and cash flows using a balance sheet approach.

Next, we examine whether other factors such as variable measurements, sample composition, and estimation methods incrementally affect the predictive ability of earnings and cash flows. That is, we repeat our analysis by introducing one change at a time in our research design and check whether inferences vary. By doing so, we hope to identify other factors contributing to the conflicting findings in the literature and also document the sensitivity of inferences to alternative design choices employed in the prior literature. As we have already demonstrated that the balance sheet method introduces measurement error in our setting, for the analyses that follow we use cash flow and accrual measures derived using the cash flow statement based approach. This allows us to isolate the incremental effects of other factors beyond the difference in the measurement of cash flows.

4.1.2 Alternative definitions of earnings, cash flows, and accruals

We redo our main analysis using alternative definitions of earnings and cash flows employed in the prior literature on cash flow prediction. First, recent research (Larson, Sloan, and Giedt 2017) highlights the large degree of heterogeneity in measuring earnings and accruals among accounting researchers. Given that prior literature relies on disparate definitions to investigate the predictive ability of earnings and cash flows, we repeat our main analysis using several alternative definitions of earnings and accruals as outlined in Appendix Table A1. Across eight alternative definitions of earnings, cash flows, and accruals, we find that cash flows consistently exhibit superior predictive ability for future cash flows. Overall, our inferences remain unaltered when we use alternative definitions of earnings, cash flows, and accruals. These findings suggest that the alternative variable definitions employed in the prior literature do not contribute much to the conflicting conclusions. Second, prior research suggests that increases in one-time and non-operating items over time explain most of the overall decline in the negative correlation between accruals and cash flows (Bushman et al. 2016). Hence, it is possible that earnings devoid of one-time and non-operating items are more potent in predicting future cash flows. Therefore, we compare the predictive ability of cash flows and earnings using the following three different measures of earnings that exclude one-time and non-operating items: (i) operating income before depreciation, (ii) operating income after depreciation, and (iii) the difference between pretax income and income from special items.⁷ Appendix Table A2 documents the results using these alternative definitions of earnings that exclude one-time, non-operating, and special items. We find that excluding such items improves the ability of earnings to predict future cash flows, but, on average, cash flows still outperform earnings.

Among the alternative measures of earnings, we find that earnings defined as operating income before depreciation exhibits superior predictive ability for future cash flows. However, this is not surprising as operating income before depreciation is, by construction, closer to operating cash flows than other measures of earnings outlined above. In fact, the Pearson correlation between operating income before depreciation and cash flow from operations is 0.74 (p<0.01). We also investigate the predictive ability of special items for future cash flows. We find that special items on average are positively related to future cash flows with predictive ability ranging from 0-4 percent over our sample period but do not exhibit any time trends. Overall, our evidence suggests that the superior predictive ability of cash flows when compared to earnings is not attributable to the one-time and non-operating items.

⁷ We compute our three measures of earnings using the following COMPUSTAT variables: (i) operating income before depreciation (OIBDP), (ii) operating income after depreciation (OIADP), and (iii) the difference between pretax income and income from special items (PI – SPI).

Third, our main analysis examines the predictability of operating cash flows following prior literature (e.g., Dechow, Kothari, and Watts 1998; Kim and Kross 2005). However, the FASB does not explicitly state the type and definition of cash flows being referenced within the conceptual framework. It is possible that investors care more about predicting free cash flows for valuation purposes than they care about predicting operating cash flows. Even though operating cash flows are the most crucial component of free cash flows, we specifically investigate the predictability of free cash flows as an additional check. We define free cash flows as cash generated by the firm's operations minus the cash paid for capital expenditures and other investments in the firm's operations (Koller, Goedhart, and Wessels 2016).⁸ We repeat all our model estimations after replacing operating cash flows with free cash flows. The results are tabulated in Appendix Table A3. We find that current free cash flows are superior to earnings in predicting future free cash flows. Overall, results from our estimations using free cash flows support our inferences based on estimations using operating cash flows.

4.1.3 Firm-specific time-series vs. cross-sectional estimations

Prior research (e.g., Finger 1994; Lorek and Willinger 1996) indicates that firm-specific time-series estimations outperform the cross-sectional models that are more popular in the literature (e.g., Kim and Kross 2005). Finger (1994), using a small sample of 50 firms and firm-specific time-series estimations, finds that cash flows outperform earnings in predicting future cash flows over short horizons. Therefore, we redo our main analysis with firm-specific time-series regressions.

 $^{^{8}}$ We assume that firms manage cash optimally and all assets are operating assets. Under these assumptions, free cash flows are defined as cash flows from operations – increase in required cash + cash interest paid – tax shield – cash flow from investing.

First, we estimate our models for each firm separately over the entire sample period (1989-2015) and then compute the average R^2 for each model based on the estimations. We then compare the predictive ability of earnings and cash flows for future cash flows using the average R^2 computed for the respective models. In our initial analysis, we impose the constraint that a firm should have at least 12 observations for reliable time-series regression estimation. We then repeat the estimations several times by increasing the minimum observations per firm threshold to 16, 20, 24, and 27. Given that our sample period comprises 27 years spanning the period 1989-2015, a minimum constraint of 27 observations per firm technically imposes the restriction that a given firm has data available for the entire sample duration (i.e., equivalent to a constant sample analysis).

We tabulate our results in Appendix Table A4. We find that cash flows outperform earnings in predicting future cash flows in all our estimations irrespective of the minimum observation constraint imposed, although the differences in predictive abilities are quite modest compared to those in the cross-sectional estimations. For example, using firm-specific regressions that require 27 observations per firm, we find that the average R^2 for the cash flow (earnings) based model is about 16 percent (14 percent).

4.1.4 Sample selection

Prior studies on cash flow predictability use various sample selection mechanisms. Specifically, some studies use a subset of large firms, while others include the full Compustat universe of firms (e.g., Finger 1994; Lorek and Willinger 1996; Barth, Cram, and Nelson 2001). Furthermore, it is possible that the increasing tendency of the Compustat dataset to include smaller and less profitable firms confounds some of our inferences. Therefore, we perform additional analysis after partitioning our sample based on firm size. Specifically, we rely on two different techniques for partitioning firms based on size. First, we partition the sample based mainly on whether a firm was included in the S&P 500 or not. Firms are included in the S&P 500 index based on market capitalization. Hence, our partition based on the S&P 500 index listing separates out the 500 largest firms in each year from the rest of the firms. We repeat our main analysis for S&P 500 and non-S&P 500 firms separately. As an additional check, we follow prior research (Dichev and Tang 2008) and split our sample based on total assets. More specifically, we identify the top 1000 firms in the sample based on total assets every year. We estimate our models for the top 1000 firms and the remaining firms separately and find that our results are not sensitive to partitioning based on firm size as measured by total assets.⁹ Appendix Table A5 (Panels A-D) presents the results. We find that, regardless of the sample composition, cash flows are superior to earnings in predicting future cash flows. Therefore, differences in sample composition among prior studies are unlikely to explain the mixed evidence on cash flow predictability.

Next, we repeat our main analysis using a constant sample of 748 firms for which we have data spanning the entire 1990-2015 period. Panel E of Table A5 presents the results. We find that the predictive ability of cash flows for future cash flows exceeds or equals that of earnings in every sample year. Further, the predictive ability of cash flows for future cash flows is increasing over time, and this trend is statistically significant. In summary, results from constant sample analysis strongly support the conclusion that cash flows are superior to earnings in predicting future cash flows. We exercise caution in interpreting the results based on the constant sample analysis, as the sample is more likely to comprise large and profitable firms (i.e., it induces survivorship bias) that are not necessarily representative of all firms in the economy.

⁹ For the partition based on total assets, we start our sample period from 1990 as our analysis requires more than 1000 firms per sample year with all data available.

Overall, the evidence suggests that cash flows consistently dominate earnings in their ability to predict future cash flows. Further, we reconcile the mixed findings in the prior literature by indicating that they are an artifact of measurement error introduced by using the balance sheet method of estimating accruals. Finally, our findings are not sensitive to alternative design choices with regard to variable definitions, sample composition, and estimation methods used in the prior literature.

4.2 Cash flow predictability over time

In this section, we investigate changes in the explanatory power of various cash flow prediction models over time. The changing contemporaneous correlation between accruals and cash flows and increasing managerial estimates in accruals may affect the predictive ability of accruals – and therefore of earnings – for future cash flows. Specifically, the declining trend in contemporaneous correlation between accruals and cash flows could have two possible effects on the ability of earnings to predict future cash flows. On one hand, this trend could decrease the ability of earnings to predict future cash flows. This is because, as Bushman et al. (2016) point out, one-time and non-operating items have increased over time, which in turn may introduce noise in accruals and result in a lower predictive ability of earnings. On the other hand, declining contemporaneous accruals-cash flows correlation could *improve* the ability of earnings to predict future cash flows. The lack of contemporaneous accruals-cash flows correlation implies that accruals and cash flows have become more orthogonal and hence likely capture different dimensions of firm performance, thereby improving earnings' predictive ability. Similarly, an increase in managerial estimates in accruals could increase earnings' ability to predict future cash flows to the extent managerial estimates embed relevant forward-looking information. However, managerial opportunism in accrual estimation could impair the predictive ability of earnings.

Therefore, the implications of these temporal shifts for cash flow predictability over time are ambiguous and warrant further empirical analysis.

Panel A of Table 5 (columns (1)-(2)) presents the coefficient estimates and explanatory power of earnings to predict future cash flows. We find that the predictive ability of earnings for future cash flows has steadily increased over time. Specifically, the explanatory power of current earnings in predicting future cash flows increases from 14 percent in 1989 to 37 percent in 2015. On average, explanatory power increases by 0.96 percent per year.

Next, we investigate trends in the ability of earnings components (cash flows and accruals) to predict future cash flows. To do so, we estimate the following specification:

$$CF_{i,t} = \beta_0 + \beta_1^{ACC} ACC_{i,t-1} + \beta_1^{CF} CF_{i,t-1} + \varepsilon_{i,t}$$

$$(3)$$

where *ACC* is total operating accruals. All other variables are as defined earlier. The results from the yearly regressions are documented in Table 6 (column (1)). We find that disaggregating earnings into cash flows and accruals increases the explanatory power of the model. In particular, the explanatory power of the disaggregated model increases from 29 percent in 1989 to 53 percent in 2015. On average, the explanatory power of the disaggregated earnings model is 1.6 times that of the aggregate earnings model (refer to Panel A of Table 5). Regarding predictive ability over time, the explanatory power of the disaggregated model increases on average by 0.98 percent per year. Overall, the evidence suggests that the ability of earnings and its disaggregated components to predict future cash flows is increasing over time.

Ex ante, it is not clear whether the increasing predictive ability of earnings for future cash flows is entirely driven by the fact that cash flows are a component of earnings, or whether accruals provide any orthogonal information over and above the information in cash flows for predicting future cash flows. To understand the increasing trend in the predictive ability of earnings and its components for future cash flows, we investigate the time trends in current cash flows' and accruals' ability to predict future cash flows, both individually and incrementally to each other. Columns (2) and (3) of Table 6 present the explanatory power of cash flows and accruals, respectively. We find that the explanatory power of current operating cash flows increases from 28 percent in 1989 to 51 percent in 2015. In other words, explanatory power increases by 0.96 percent per year on average. At the same time, the explanatory power of accruals drops from 7 percent in 1989 to 0 percent in 2015 (column (3)). In fact, the explanatory power of accruals after 1999 is zero for most years (except for years 2002, 2004, 2005, 2008, and 2012, in which the explanatory power is a paltry 1 percent). In terms of the explanatory power over time, we find a decline of approximately 0.16 percent per year, and this decline is statistically significant.

To investigate the incremental explanatory power of the two main earnings components, we compute the incremental Adj. R^2 of cash flows (accruals) by subtracting the Adj. R^2_{ACC} (Adj. R^2_{CF}) reported in column (3) ((2)) from the multivariate Adj. R^2 reported in column 1. These results are documented in columns (4) and (5) of Table 6. We find that the incremental explanatory power of cash flows ranges from 22 percent to 55 percent. This explanatory power is increasing over time at the rate of 1.14 percent per year, and this trend is statistically significant. In contrast, the incremental explanatory power of accruals ranges from 1 to 3 percent. Further, we do not observe any trend in the incremental predictive ability of accruals. This evidence suggests that both accruals and cash flows uniquely contribute to predicting future cash flows; however, the incremental explanatory power of accruals is markedly lower. The incremental explanatory power of accruals. Thus, the increase in earnings' ability to predict future cash flows over time is attributable to the increase in current cash flows' ability to predict future cash flows. Together, the findings presented above

suggest that the changing accrual properties do not drive the time-series trend in earnings' predictive ability for future cash flows.

These time-series patterns are robust to various design choices such as alternative definitions of earnings, cash flows, and accruals; time-series analysis versus cross-sectional tests; and alternative samples. Appendix Tables A1-A5 present these results.

Overall, there is robust evidence that the ability of both earnings and cash flows to predict future cash flows is increasing over time, and this increasing trend is both economically and statistically significant. However, accruals have little incremental information content over cash flows in predicting future cash flows, and this has not changed over time. Therefore, the increasing ability of earnings to predict future cash flows is attributable to cash flows rather than accruals.

4.3 Cash flow predictability: Evidence from disaggregated components of accruals4.3.1 Cash flow predictability: Accrual components

So far, our evidence suggests a lack of substantial incremental information or significant time trends in accruals' ability to predict future cash flows, over and above the predictive ability of current cash flows. However, prior research (e.g., Barth, Cram, and Nelson 2001) finds that disaggregating accruals into its major components enhances the predictive ability of accruals for future cash flows. In light of this finding, we next investigate whether the predictive ability of disaggregated accrual components for future cash flows changes over time. To do so, we estimate the following empirical specification by year:

$$CF_{i,t} = \beta_0 + \beta^{\text{CHG}_AR} CHG_AR_{i,t-1} + \beta^{\text{CHG}_INV} CHG_INV_{i,t-1} + \beta^{\text{CHG}_AP} CHG_AP_{i,t-1} + \beta^{\text{DEPR}} DEPR_{i,t-1} + \beta^{\text{AMORT}} AMORT_{i,t-1} + \beta^{\text{OTHER}} OTHER_{i,t-1} + \varepsilon_{i,t}$$
(4)

where *CHG_AR* is change in accounts receivable; CHG_INV is change in inventory; CHG_AP is change in accounts payable; DEPR is depreciation expense; AMORT is amortization expense; OTHER is net of all other accruals. On average, an increase in accounts receivable and an

increase in inventory should be positively related to future operating cash flows, whereas an increase in accounts payable should be negatively related to future operating cash flows (Barth et al. 2001). Depreciation and amortization should have positive signs under certain conditions. As these expenses are related to long-term investments, on average, it is reasonable to assume that firms make such investments with the expectation of generating higher cash flows. Further, according to the matching principle, the higher the costs are, the higher the benefits should be. If return on investment is greater than the cost of capital, higher depreciation and amortization implies higher cash flows. Therefore, these variables are expected to have a positive coefficient when predicting future cash flows (Feltham and Ohlson 1996; Barth et al. 2001).

We estimate the above specification both with and without including lagged cash flows as an additional predictor variable, and we tabulate our results in Table 7. The explanatory power of the disaggregated accrual components is higher than that of total accruals in each of the years 1989-2015. Specifically, the explanatory power of the disaggregated model, as reported in Table 7, Panel A column (1), is 14 percent in 1989, and it decreases to 3 percent in 2015. In contrast, as reported in Table 6 column (3), the explanatory power of total accruals is 7 percent in 1989, and it decreases to 0 percent in 2015. The decline in explanatory power over time is steeper for the disaggregated model than for the total accrual model. Specifically, the explanatory power declines by 0.23 percent (0.16 percent) per year for the disaggregated (aggregated) accrual model.

Next, we augment the above specification by adding lagged cash flows as an additional independent variable to evaluate the incremental predictive ability of disaggregated accrual components for future cash flows. The results are documented in column (2) of Table 7, Panel A. We find that the predictive ability of cash flows and accrual components together increases from 33 percent in 1989 to 54 percent in 2015. The incremental explanatory power of the accrual

components over current cash flows is tabulated in column (3). It is estimated as the difference between column (2) of Table 7, Panel A and column (4) of Table 5, Panel A. We find that the incremental predictive ability of disaggregated accrual components ranges between 2 percent and 8 percent. Further, accrual components' incremental ability to predict cash flows declines by 0.07 percent per year.¹⁰

In contrast, the incremental predictive ability of cash flows over disaggregated accrual components increases from 19 percent in 1989 to 51 percent in 2015 (see column (4) of Table 7, Panel A). In other words, the incremental explanatory power of cash flows increases by about 1.13 percent per year. Overall, the results from disaggregating accruals into its components are qualitatively similar to those using total accruals, with regard to the incremental information content and time trends in predictability of future cash flows. These findings further reinforce our argument that the factors that drive accrual properties to vary over time have little effect on the trends in earnings' ability to predict future cash flows. Rather, any observed trend in the predictive ability of earnings is likely due to cash flow specific factors.

4.3.2 Cash flow predictability: disaggregated components of accruals based on magnitude of estimation

In our earlier analysis, we documented that the increasing predictive ability of earnings for future cash flows over time is largely driven by trends in the predictive ability of cash flows and not accruals or disaggregated accruals per se. However, recent research by Lev, Li, and Sougiannis (2010) suggests that managerial estimates embedded in accruals impact the usefulness of such measures in predicting future cash flows. Hence, we disaggregate accruals based on the extent to

¹⁰Appendix Table A6 provides the estimation coefficients of the model. As this table shows, we find that most of the disaggregated accrual components have coefficient signs consistent with our prediction with the exception of amortization expense. Nevertheless, we advise caution when drawing inferences based on time trends in incremental R^2 of accrual components.

which accruals are affected by managerial estimates. Specifically, we distinguish between accruals that are based primarily on estimates (ACC_EST) and those that are largely unaffected by estimates (ACC_DELTA). Following prior research (Lev et al. 2010), we consider changes in working capital accruals excluding inventory to be unaffected by managerial estimates, and we consider the remaining accruals (i.e., inventory and other non-working capital accruals) to be based primarily on estimates. We estimate the following specifications by year and tabulate our results in Table 7, Panel B:

$$CF_{i,t} = \beta_0 + \beta^{CF} CF_{i,t-1} + \varepsilon_{i,t}$$
⁽⁵⁾

$$CF_{i,t} = \beta_0 + \beta^{\text{CF}} CF_{i,t-1} + \beta^{\text{ACC_EST}} ACC_EST_{i,t-1} + \varepsilon_{i,t}$$

$$(6)$$

$$CF_{i,t} = \beta_0 + \beta^{CF} CF_{i,t-1} + \beta^{ACC_DELTA} ACC_DELTA_{i,t-1} + \varepsilon_{i,t}$$
(7)

$$CF_{i,t} = \beta_0 + \beta^{\text{CF}} CF_{i,t-1} + \beta^{\text{ACC_EST}} ACC_EST_{i,t-1} + \beta^{\text{ACC_DELTA}} ACC_DELTA_{i,t-1} + \varepsilon_{i,t}$$
(8)

The following insights emerge. First, we find that any incremental contribution to the prediction of future cash flows stems from accruals not influenced by managerial estimates (ACC_DELTA). The incremental contribution of accruals based on managerial estimates (ACC_EST) to the prediction of future cash flows is nearly zero in every single year (see column (5) of Table 7 Panel B). Second, we find that neither of the accrual categories exhibits any systematic trend in predicting future cash flows over time. Overall, our results indicate that disaggregating accruals based on embedded managerial estimates does not affect our earlier inference that trends in the predictive ability of earnings for future cash flows are mainly due to current cash flows and not accruals.

4.4 Potential explanations of the time-series patterns in cash flow prediction ability

Given that the incremental predictive ability of accruals for future cash flows does not exhibit any time trend, we conjecture that factors specific to accruals such as trends in conservatism, earnings manipulations, and increasing complexity associated with estimating accruals are less likely to explain the increasing predictive ability of cash flows. Therefore, we focus on trends in cash flow-related factors that could improve the predictive ability of cash flows for future cash flows. Following prior theoretical and empirical literature (e.g., Dechow et al. 1998; Bushman et al. 2016), we examine how temporal shifts in the following three explanatory variables are associated with the changing ability of cash flows to predict future cash flows: (i) operating cycle, (ii) working capital, and (iii) intangible intensity.

Theoretical literature suggests that the relative predictive ability of earnings and cash flows is a function of firms' operating cash cycles and working capital policies (Dechow et al. 1998). Specifically, longer operating cycles increase the variance in forecast error of cash flow based models relative to earnings based models when predicting future cash flows. Working capital accruals help offset negative serial correlation in cash flow changes, thereby improving the relative predictive ability of earnings over cash flows for cash flow predictability (Dechow 1994). It follows that the relative predictive ability of earnings over cash flows decreases with the length of the operating cycle and the magnitude of working capital accruals. Finally, growing investments in intangibles increase cash flows' ability to predict future cash flows, as these investments do not often generate accruals due to the immediate expensing of these items (Bushman et al. 2016). Therefore, we expect cash flows' predictive ability to increase with intangible intensity. Since accruals' predictive ability is not changing over time, accrual-specific factors (e.g., one-time special items and non-operating income, matching between revenues and expenses) are unlikely to explain the increasing predictive ability of cash flows. Therefore, we do not analyze these factors for exploring time trends in cash flows predictability.

For each year in our sample period, we compute the cross-sectional median length of the operating cycle of a firm (OperCyc) and the cross-sectional median working capital excluding cash and short-term securities (WorkCap), and we use the amount of selling, general and administrative expenses (SG&A) to measure intangible intensity. Table 2 provides detailed descriptions of all our determinant variables, and the descriptive statistics for these variables appear in Table 8 Panel A.

Next, we investigate whether these explanatory variables display any time trend over the sample period. To determine the time trend, we regress each of our explanatory variables on a *Time* variable, which takes the value of 1 through 27 for the years 1989-2015, and we tabulate our results in Table 8 Panel B. We find that operating cycle (OperCyc) and working capital accruals (WorkCap) are declining over time. Specifically, operating cycle is declining by 0.47 days per year, and working capital accruals as a percentage of total assets are declining by 0.42 percent per year. These declining trends are statistically significant at the 1 percent level or better. In contrast, the intensity of intangibles (SG&A) is increasing over time. Specifically, the SG&A expense as a percentage of total expenses increases by 0.10 percent per year. At first blush, these descriptive statistics suggest that these changing patterns could potentially explain the changing predictive ability of cash flows.

To measure the association between each of our explanatory variables and the improving predictive ability of cash flows, we estimate the following specification:

Adj.
$$R^{2}_{CF} = \beta_{0} + \beta_{1} * Time + \sum \beta_{j} * Factor_{j} + \varepsilon$$
 (9)

where Adj. R^{2}_{CF} refers to the annualized measure of Adj. R^{2} computed by regressing cash flows on future cash flows (as documented in Table 5, Panel A, column (4)); *Factor* refers to each of the three determinant variables, and *Time* takes the value of 1 through 27 for the years 1989-2015. Panel C of Table 8 presents the results. Columns (1)-(3) provide the univariate association between each of our explanatory variables and cash flow predictive ability (Adj. R^2_{CF}). We find that decreases in operating cycle and working capital accruals are associated with increases in the predictive ability of cash flows for future cash flows. Further, we find that intangible intensity is positively associated with the ability of cash flows to predict future cash flows, consistent with Bushman et al. (2016).

In column (4), we estimate a specification that includes all three explanatory variables along with the time trend. We find that the coefficient estimate on *Time* is not zero and statistically significant. This suggests that the explanatory variables we consider can only partly explain the time trend in the predictive ability of cash flows for future cash flows. We find that operating cycle is the dominant factor across the three variables that we explore. However, we exercise caution in interpreting the coefficients in our full specification as multi-collinearity among the explanatory variables may affect standard errors. All our inferences are qualitatively similar if we redo the tests using the incremental R^2 as the dependent variable (see columns (5)-(8)).

Overall, our results indicate that declining operating cycles, decreasing levels of working capital accruals, and increasing levels of intangible intensity partially explain the increasing predictive ability of cash flows, with operating cycle being the dominant factor. To explore further, we examine the relation between the changes in operating cycle and the forecast horizon. Given that the average operating cycle length for our sample firms is a little over one quarter (i.e., about 115 days), we conjecture that the relative predictive ability of earnings over cash flows is likely to improve as the reporting period gets shorter. In other words, the longer the operating cycle relative to the reporting period, the greater the benefit of relying on accruals and earnings to capture the underlying economics of a firm. To test this conjecture, we repeat our main analysis using quarterly

data spanning the same sample period. More specifically, we run cross-sectional regressions to estimate the ability of quarterly earnings and cash flows to predict one-quarter-ahead cash flows, and we tabulate the results in Table 9.

Consistent with expectations, we find that the average predictive ability of earnings for future cash flows exceeds that of current cash flows for all fiscal quarters. The average predictive ability of earnings (cash flows) for future cash flows using quarterly reporting data ranges from 17 to 24 percent (11 to 16 percent). We observe a general increase in the predictive ability of both earnings and cash flows over time. Overall, our evidence suggests that the usefulness of earnings as a summary measure for predicting cash flows crucially depends on the duration of the operating cash cycle of firms in the economy and the forecasting period. We also repeat our tests at the semiannual frequency. Appendix Table A7 reports the results. As with our analysis based on quarterly reporting data, the predictive ability of earnings is superior to that of current cash flows even at the semi-annual frequency. Interestingly, the difference in predictive ability between earnings and current cash flows is lower at the semi-annual level than at the quarterly level. This evidence buttresses our argument that the length of the operating cycle relative to the reporting period plays a critical role in the relative predictive ability of earnings and cash flows for future cash flows. At the annual frequency level, where the reporting period is much longer than the operating cycle, earnings no longer exhibit superior predictive ability. It is important to note, however, that many practical applications that involve forecasting cash flows, such as valuation and credit risk analysis, often require estimation of future annual cash flows. In such scenarios, our evidence suggests that earnings do not perform better than current cash flows.

4.5 International evidence

Since our analysis thus far focuses exclusively on US firms, it begs the question of whether our findings extend to international firms that follow different accounting standards, face different capital market pressures, and encompass varying institutional environments. A reader might conjecture that our results should hold in an international setting given that cash flow-related factors rather than accrual-specific factors drive the time-series trend in earnings' predictive ability. However, since cash flow-related factors and associated trends may vary across jurisdictions, it is not obvious whether trends in cash flow predictability observed in the US setting extend to an international sample. Before we conduct cash flow prediction tests, we first investigate whether the findings in Bushman et al. (2016) extend to international sample firms obtained from the Compustat Global database. As many international firms follow the IAS standard or a derivative, statements of cash flows are available for such firms only after 1994. To facilitate reliable statistical estimations, we impose the restriction of at least 30 observations per country-year and at least 18 years of country-level data availability. We drop firms in the bottom decile of annual sales and exclude observations at the 1 percent and 99 percent levels to mitigate the effects of outliers in the international sample (Ball, Kothari, and Robin 2000; Land and Lang 2003). Our final sample includes 139,707 firm-year observations from 21 jurisdictions spanning the period 1998-2015.

The results presented in Table 10 indicate that Bushman et al.'s (2016) results do extend to international sample firms. Specifically, as documented in column (1), the negative contemporaneous correlation between accruals and cash flows has been declining over time, and this correlation has recently become positive. Next, we find that both earnings' and cash flows' ability to predict future cash flows is increasing over time (columns (3) and (4)). Specifically, earnings' (cash flows') ability to predict future cash flows increases by 1.74 (1.44) percent per year. Further, the increasing predictive ability of earnings is attributable mostly to cash flows (see columns (6) and (7)). Finally, we find that cash flows are superior to earnings in predicting future cash flows. Specifically, as documented in columns (3)-(4), current cash flows have better explanatory power than current earnings in predicting future cash flows in every single year.

However, our conclusions are predicated on the assumption that the accrual properties and attendant effects on the information content of accruals and earnings are similar across jurisdictions, which need not be the case. In particular, Barth, Landsman, and Lang (2008) find that firms applying IAS see greater improvement in the value relevance of accounting amounts than firms applying non-US domestic standards. Several prior studies suggest that the adoption of International Financial reporting Standards (IFRS) in Europe led to improvement in accounting quality and reduction in cost of capital (Armstrong, Barth, Jagolinzer, and Riedl 2010; Li 2010). To provide further insights, we repeat our international analysis using a sub-sample of firms from eight EU jurisdictions that adopted IFRS starting in 2005. Our results, tabulated in Appendix Table A8, indicate that the ability of cash flows to predict future cash flows is superior to that of earnings in both the pre-adoption (1998-2005) and the post-adoption (2006-2015) periods. Further, we observe that the predictive ability of cash flows for future cash flows increases over time during the entire sample period of 1998-2015. We also note that while the incremental predictive ability of cash flows increases during the entire sample period, there is no significant change in the incremental predictive ability of accruals. Overall, we find that the superior predictive ability of cash flows for future cash flows and the associated time trend do not seem to be limited to any specific jurisdiction, accounting standard, or subset of the sample period. This evidence is

consistent with the inference that economic factors rather than accounting standards contribute to the observed phenomenon.

Overall, we find that (i) Bushman, Lerman, and Zhang's (2016) results extend to international sample firms, and (ii) international firms exhibit trends similar to those of US firms with respect to the differential predictive ability of earnings and cash flows for future cash flows.

5. Additional Analyses

5.1 Out-of-sample tests

We also conduct out-of-sample tests to evaluate the relative predictive ability of alternative prediction models. The utility of any cash flow prediction model depends on the predictive ability demonstrated in out-of-sample tests, as practical applications such as inputs to valuation models and evaluating the liquidity and solvency of a firm employ real-time accounting numbers. For example, equity and debt analysts use projected future cash flows based on available real-time information in valuation models to assess a firm's liquidity and solvency. Therefore, we examine whether the out-of-sample cash flow prediction using prior-year earnings or accruals models is better than that using prior-year cash flow model. Appendix Table A9 presents the results. As before, we find that cash flows outperform earnings in predicting future cash flows. Also, we find that the predictive ability of accruals and earnings relative to that of current cash flows deteriorates over time, and these trends are statistically significant.

5.2 Multi-horizon cash flow predictability over time

Thus far, we have restricted our analysis to predicting one-period-ahead cash flows. In this section, we consider alternative prediction horizons: two- and three-year-ahead cash flows. Panel A (B) of Appendix Table A10 presents the results of regressing two-year- (three-year-) ahead cash flows on current earnings, current cash flows, and current accruals. The findings from the multi-horizon cash flow prediction models are comparable to those from one-year-ahead cash flow

prediction models reported in Table 5 (Panel A) and Table 6. Specifically, we find that the predictive ability of earnings and cash flows for two-year and three-year horizon cash flows has increased over time. In addition, cash flows are superior to earnings in predicting future cash flows over both two-year and three-year horizons.

5.3 Cash flow predictability over time: Cohort analysis

Srivastava (2014) documents that successive cohorts of newly listed firms exhibit higher revenues, higher cash flow volatility, and lower matching between revenues and expenses, and integrating such new cohorts into a study sample may influence various earnings characteristics. To examine whether changes in sample composition over time are driving the results in our study, we repeat our main analysis after dividing the sample firms into three separate listing cohorts. Following prior research (Srivastava 2014; Bushman et al. 2016), we define the first year in which a firm's data are available in Compustat as the "listing year." We then classify firms with a listing year before 1990 as "pre-1990." Firms listed during the periods 1990-1999 and 2000-2015 are classified as "wave 1990" and "wave 2000," respectively. For each of these cohorts, we estimate the cash flow predictability evidence over time after the listing year.

Appendix Table A11 presents the results. We find that the predictive ability of cash flows exceeds that of earnings in every year of each cohort. Further, earnings' and cash flows' ability to predict future cash flows is increasing over time. While this trend is statistically significant at the 1 percent level for the "pre-1990" and "wave 1990" cohorts, it is not significant for the "wave 2000" cohort.¹¹ Overall, our results provide reasonable assurance that the findings in the paper are not due to the cohort phenomenon documented by Srivastava (2014).

¹¹ The "wave 2000" cohort is the shortest time series among the three cohorts, and this reduces sample power in our time-series estimations.

5.4 Cash flow predictability over time: Excluding non-articulating events

Hribar and Collins (2002) point out that using the balance sheet approach introduces errors in the measurement of accruals. They identify three specific non-articulating events as potential sources of bias in accruals measurement: (i) mergers and acquisitions, (ii) divestitures, and (iii) foreign currency translations. In this section, we estimate our main models (equations (1)-(3)) using both the balance sheet approach and the cash flow statement approach after removing firmyear observations corresponding to the above-mentioned corporate events. We tabulate the results in Appendix Table A12 (see Panels A and B). In particular, we remove observations from our sample that satisfy any of the following criteria: (i) absolute value of contributions from sales (or income) from acquisitions greater than \$10,000, (ii) absolute value of discontinued operations or long-terms assets of discontinued operations greater than \$10,000, and (iii) absolute value of gain or loss from foreign currency translations greater than \$10,000.¹² We find that eliminating these observations does not change our inference. Cash flows (earnings) predict future cash flows better than earnings (cash flows) do when we use the cash flow statement (balance sheet) approach. In other words, our findings suggest that eliminating observations corresponding to non-articulating events when using the balance sheet approach does not fix the measurement error problem entirely.

5.5 Cash flow predictability over time: Industry analysis

In this section, we repeat our main analysis for each major industry to compare trends in cash flow predictability across industries and tabulate the results of our estimations in Appendix Table A13. We categorize the firms in our sample based on the Fama-French 10-industry classification.¹³ We find that the predictive ability of current cash flows for future cash flows

¹² We use the following Compustat items to check for non-articulation observations: AQI (Income from acquisitions), AQS (Sales from acquisitions), DO (Discontinued operations), ALDO (Long-term assets of discontinued operations), & FCA (gain or loss from foreign currency translations).

¹³ http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_10_ind_port.html

exceeds that of current earnings in all industry groups. The incremental predictive ability of cash flows is also increasing over time, except in the case of the Telecom industry where there is no observed time trend. Overall, we find that our main results are not driven by any specific industry group but rather reflect economy-wide trends over time.

5.6 Cash flow predictability: Disaggregating accruals based on financial statement source

Following Casey et al. (2017), we disaggregate accruals based on the source of the financial statement (i.e., cash flow statement, statement of shareholder equity, and balance sheet). Using these disaggregated accruals, we repeat our main analyses and find similar results. Appendix Table A14 presents the results. We find that the incremental predictive ability of disaggregated accruals ranges from 1 to 4 percent but does not display any time trend. In contrast, the incremental predictive ability of cash flows over disaggregated accruals ranges from 11 percent to 45 percent and increases at the rate of 0.99 percent per year over the sample period. We fail to find temporal trends in the predictive ability of accruals for cash flows regardless of the financial statement source. This supports our inference that the increasing predictive ability of earnings over time is primarily due to temporal trends in cash flows and not accruals.

5.7 Cash flow predictability: Macroeconomic conditions

In the main analysis, we observe non-monotonic but almost similar temporal patterns in the predictive ability of cash flows and earnings for future cash flows. We expect changes in economic factors rather than accounting standard-specific factors to drive these patterns. To provide additional evidence in support of our conjecture, we perform the following analyses. First, we investigate how predictive abilities vary according to business cycles. Appendix Table A15 presents the results. We find that both earnings and cash flows have lower predictive ability during recessions than during expansionary periods. In particular, the average predictive ability of earnings (cash flows) is 0.19 (0.30) percent during recessions, which is significantly lower than
the explanatory power of 0.25 (0.38) percent during expansions. This is consistent with the possibility that during recessionary periods, operating cycles will increase leading to a reduction in predictive ability of both earnings and cash flows. Second, we also investigate how the predictive ability varies based on the aggregate economic uncertainty. Specifically, we employ economic policy uncertainty as a measure of aggregate uncertainty (Baker et al. 2016). We classify periods with above sample median uncertainty index as high uncertainty and other periods as low uncertainty. We find that the predictive ability of both earnings and cash flows is lower in high-uncertainty periods than in low-uncertainty periods.

6. Conclusion

We find that cash flows do a better job of predicting future cash flows than earnings every year during the period 1989-2015. This finding stands in stark contrast to several papers that document the opposite. The contradiction in the findings is attributable to measurement error in computing operating cash flows using the balance sheet approach rather than directly obtaining from the cash flow statement. Our finding has implications for accounting educators, academics, practitioners, and policy setters as it questions prior beliefs about the usefulness of financial information and challenges common wisdom that earnings are superior to cash flows in predicting future cash flows.

We also investigate the implications of the changing landscape of accrual accounting for trends in cash flow predictability. Using both a US sample and an international sample, we find that earnings' ability to predict future cash flows is increasing over time. However, this trend is largely attributable to the increasing ability of cash flows, rather than accruals, to predict future cash flows. The increasing ability of cash flows to predict future cash flows is associated with decreasing operating cycles, decreasing working capital, and increasing intangible intensity over time. We conjecture that other forces such as globalization, technological innovations, better working capital management, relative use of intangible and physical assets, and better inventory management may also contribute to these time trends. We leave a more detailed evaluation of these factors to future research.

Our results also suggest other avenues for further research. First, in our analysis, we investigate the prediction of future cash flows rather than future stock prices or stock returns.¹⁴ As Bushman et al. (2016) mention in their study, the implications of the changing landscape of accrual accounting for stock prices and returns is still an open question. Second, prior studies that predict aggregate stock returns using aggregate cash flows and accruals (e.g., Hirshleifer, Hou, and Teoh 2009; Kang, Liu, and Qi 2010) utilize the balance sheet based approach for estimating cash flows and accruals. At least one source of measurement error in the balance sheet approach (i.e., mergers and acquisitions) is likely correlated with aggregate market returns. However, the extent of measurement error and how it affects the relations between aggregate cash flows, accruals, and aggregate returns remain unknown. While Hribar and Collins (2002) do point to the effects of measurement error, our findings suggest that the implications of the measurement error are much more far-reaching than previously recognized in the literature. The time trends in the usefulness of accruals coupled with the importance of measuring cash flows correctly beg the question of whether the debate about the accruals versus cash flow anomaly proposed by Desai et al. (2004) should be revisited. Finally, findings in the paper have implications for studies that examine trends in the value relevance of accounting information for equity and debt markets. In particular, prior literature documents that the value-relevance of earnings has been steadily declining for equity

¹⁴ Our assumption of realized cash flows as a proxy for expected cash flows assumes rational expectations, as in prior literature in different contexts (e.g., Penman and Sougiannis 1998; Aboody, Barth, and Kasznik 1999; Barth et al. 2001).

markets (e.g., Collins, Maydew, and Weiss 1997) while simultaneously improving for debt markets (e.g., Givoly, Hayn, and Katz 2017). Given the increase in cash flow persistence and the relatively little change in the predictive ability of accruals over time, researchers have to exercise caution in attributing changes in the value relevance of earnings to economic versus accounting forces.

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Table 1: Summary of relevant literature

Ν	Paper	Sample Years	Measurement	Research Design	Which Measure is Better?
1	Brooks (1982)	30 firms	B/S Method	Time-series regressions; annual frequency	Earnings
2	Bowen, Burgstahler, and Daley (1986)	1971-1981	B/S method	Cross-sectional regressions; annual frequency	Cash flows
3	Greenberg, Johnson, and Ramesh (1986)	1964-1982	B/S method	Cross-sectional regressions; annual frequency	Earnings
4	Finger (1994)	1935-1987 (50 firms)	B/S method	Time-series regressions; annual frequency	Cash flows (in the short-run; earnings and cash flows have similar performance over the long run)
5	Lorek and Willinger (1996)	1979-1991 (51 firms)	B/S method	Time-series & cross-sectional regressions; quarterly frequency	Earnings
6	Burgstahler, Jiambalvo, and Pyo (1998)	1988-1996	C/F method	Cross-sectional regressions; annual frequency	Cash flows
7	Dechow, Kothari, and Watts (1998)	1963-1992	B/S method	Time-series & cross-sectional regressions; annual frequency	Earnings
8	Kim and Kross (2005)	1973-2000	B/S method	Cross-sectional regressions; annual frequency	Earnings
9	Subramanyam and Venkatachalam (2007)	1988-2000	C/F method	Cross-sectional regressions; annual frequency	Cash flows
10	Lorek and Willinger (2009)	1990-2004	C/F method	Time-series & cross-sectional regressions; annual frequency	Cash flows
11	Nam, Brochet, and Ronen (2012)	1987-2006	C/F method	Time-series regressions; quarterly frequency	Earnings
12	Chen, Melessa, and Mergenthaler (2017)	1988-2016	C/F method	Cross-sectional regressions; annual frequency	Cash flows

Earnings or cash flows: Which measure predicts future cash flows better?

Incremental predictive ability of accruals

Ν	Paper	Sample Years	Measurement	Research Design	Conclusion
1	Barth, Cram, and Nelson (2001)	1987-1996	C/F method	Cross-sectional regressions; annual frequency	Disaggregated accruals improve predictive ability.
2	Lev, Li, and Sougiannis (2010)	1988-2004	C/F method	Cross-sectional regressions; annual frequency	Decompose total accruals into accruals with little estimation and accruals with substantial estimation and projections. Accruals overall help improve predictions, but the accrual components with substantial estimations and projections do not.
3	Nam, Brochet, and Ronen (2012)	1987-2006	C/F method	Time-series regressions; quarterly frequency	Accruals have incremental predictive ability over cash flows in predicting future cash flows.
4	Barth, Clinch, and Israeli (2016)	1989-2013	C/F method	Cross-sectional regressions; annual frequency	Portioning accruals based on their role in cash flow alignment improves cash flow predictability.

Trends in predictive ability

N	Paper	Sample Years	Measurement	Research Design	Is There a Trend in Predictability?
1	Kim and Kross (2005)	1973-2000	B/S method	Cross-sectional regressions; annual frequency	Yes. Earnings' ability to predict cash flows is increasing over time. The trend in cash flows' ability to predict future cash flows is lower than the trend in earnings' predictive ability.
2	Lorek and Willinger (2009)	1990-2004	C/F method	Time-series & cross-sectional regressions; annual frequency	No. Neither earnings nor cash flows exhibit time trends in predictive ability.

Table 2: Variable descriptions

Variable	Description
EARN	Income before extraordinary items and discontinued operations [Compustat: IB].
CF	Net cash flow from operating activities less cash flow from extraordinary items and discontinued operations [Compustat: <i>OANCF – XIDOC</i>].
ACC	Total operating accruals, estimated as income before extraordinary items and discontinued operations minus net cash flow from operating activities less cash flow from extraordinary items and discontinued operations [Compustat: $EARN - CF$].
ACC (B/S Approach)	Total accruals estimated using a balance sheet approach: computed as changes in noncash current assets [Compustat: ACT-CHE] minus changes in non-debt current liabilities [Compustat: LCT-DLC] minus depreciation expense [Compustat: DP].
CF (B/S Approach)	Cash flows from operations computed as income before extraordinary items and discontinued operations minus total accruals computed using the B/S approach [IB – ACC (B/S Approach)].
CHG_AR	Change in accounts receivable [Compustat: - <i>RECCH</i>]. Missing values are set to zero.
CHG_INV	Change in inventory [Compustat: -INVCH]. Missing values are set to zero.
CHG_AP	Change in accounts payable [Compustat: APALCH]. Missing values are set to zero.
DEPR	Depreciation expense [Compustat: XDP, DP-AM]. Missing values are set to zero.
AMORT	Amortization expense [Compustat: AM, DP-XDP-XDEPL]. Missing values of XDEPL are set to zero.
OTHER	Net of all other accruals calculated as [ACC - (CHG_AR + CHG_INV - CHG_AP – DEPR - AMORT)].
ACC_DELTA	Accruals that are largely unaffected by estimates (i.e., changes in working capital items, excluding inventory) [Compustat: -(RECCH+APALCH+TXACH+AOLOCH].
ACC_EST	Accruals primarily based on estimates (i.e., most non-working capital accruals and inventory) [ACC – ACC_DELTA].
OperCyc	The cross-sectional median length of the operating cycle of a firm. Operating cycle is calculated as (365/Sale)*Average Accounts Receivable + (365/COGS)* Average Inventory [Compustat: SALE, RECT, COGS, INVT].
WorkCap	The cross-sectional median of working capital accruals scaled by average assets. Working capital accruals are estimated as (current assets – cash and cash equivalents – short-term marketable securities – current liabilities) [Compustat: ACT – CHE – LCT].
SG&A	SG&A Intensity, a proxy for intangible intensity, measured as SG&A expenses scaled by total expenses (sales minus earnings before extraordinary items) [Compustat: XSGA, SALE, IB].

Variable	Ν	Mean	SD	P25	Median	P75	Min	Max
EARN	118,624	0.017	0.135	-0.007	0.037	0.079	-0.999	0.366
CF	118,624	0.076	0.115	0.030	0.081	0.135	-0.498	0.407
ACC	118,624	-0.059	0.106	-0.097	-0.051	-0.013	-0.821	0.318
CHG_AR	118,624	0.015	0.052	-0.004	0.005	0.026	-0.204	0.341
CHG_INV	118,624	0.009	0.039	-0.001	0.000	0.013	-0.152	0.249
CHG_AP	118,624	0.008	0.037	-0.002	0.000	0.015	-0.154	0.235
DEPR	118,624	0.030	0.032	0.000	0.024	0.046	0.000	0.173
AMORT	118,624	0.004	0.010	0.000	0.000	0.004	0.000	0.138
OTHER	118,624	-0.039	0.082	-0.063	-0.024	0.000	-0.672	0.245

Table 3: Descriptive statistics

Table 3 reports descriptive statistics for key variables. The sample spans 27 years from 1989 to 2015. All variables are described in Table 2. All continuous variables are winsorized at the 1 percent and 99 percent levels. All variables are deflated by the average book value of total assets.

	EARN	CF	ACC	CHG_AR	CHG_INV	CHG_AP	DEPR	AMORT	OTHER
EARN		0.592	0.360	0.222	0.199	0.120	-0.004	-0.041	0.224
CF	0.632		-0.398	-0.080	-0.123	0.098	0.181	0.007	-0.139
ACC	0.554	-0.269		0.328	0.360	-0.017	-0.220	-0.061	0.507
CHG_AR	0.166	-0.144	0.367		0.210	0.357	-0.032	-0.003	-0.109
CHG_INV	0.144	-0.197	0.393	0.234		0.232	-0.032	-0.026	-0.011
CHG_AP	0.043	0.047	0.000	0.431	0.314		0.004	-0.042	0.032
DEPR	-0.038	0.179	-0.242	-0.043	-0.052	-0.002		0.265	0.303
AMORT	-0.161	-0.040	-0.159	-0.020	-0.046	-0.040	0.036		0.131
OTHER	0.488	-0.043	0.666	-0.104	-0.015	0.023	0.148	-0.033	

Table 4: Correlation matrix

Table 4 presents the Spearman (above diagonal) and Pearson (below diagonal) correlation coefficients for all variables. The sample spans 27 years from 1989 to 2015 (N=118,624). All variables are described in Table 2. All continuous variables are winsorized at the 1 percent and 99 percent levels. Values in bold indicate statistical significance at 1 percent or better.

$CF_{i,t} =$	$\beta_0 + \beta^{EA}$	$ERN_{i,t-1} + \varepsilon_{i,t}$	$\beta_0 + \beta^{\mathrm{CF}} CF_{i,t-1} + \varepsilon_{i,t}$		
Year	β^{EARN}	Adj. R ² _{EARN}	β^{CF}	Adj. R ² _{CF}	
	(1)	(2)	(3)	(4)	
1989	0.54	0.14	0.54	0.28	
1990	0.45	0.14	0.51	0.24	
1991	0.41	0.13	0.52	0.23	
1992	0.37	0.11	0.54	0.26	
1993	0.38	0.12	0.56	0.28	
1994	0.41	0.15	0.60	0.30	
1995	0.39	0.13	0.54	0.28	
1996	0.46	0.16	0.57	0.25	
1997	0.50	0.23	0.61	0.33	
1998	0.41	0.18	0.62	0.35	
1999	0.44	0.23	0.60	0.33	
2000	0.55	0.23	0.69	0.29	
2001	0.38	0.22	0.58	0.31	
2002	0.33	0.22	0.63	0.37	
2003	0.45	0.31	0.67	0.41	
2004	0.60	0.34	0.75	0.48	
2005	0.56	0.32	0.69	0.43	
2006	0.60	0.34	0.75	0.47	
2007	0.54	0.32	0.65	0.41	
2008	0.53	0.29	0.64	0.38	
2009	0.31	0.19	0.58	0.33	
2010	0.44	0.24	0.64	0.37	
2011	0.54	0.28	0.71	0.38	
2012	0.64	0.36	0.79	0.50	
2013	0.54	0.31	0.79	0.47	
2014	0.63	0.42	0.79	0.53	
2015	0.54	0.37	0.74	0.51	
Average		0.24		0.36	
Trend (t-value)		0.0096*** [8.34]		0.0096*** [8.32]	

Table 5: Cash flow predictability over time

Panel A: Cash flow predictability using lagged earnings and lagged cash flows: Cash flows estimated using cash flow statement

$CF_{i,t} =$	$\beta_0 + \beta^{EA}$	$\mathbb{E}^{RN}EARN_{i,t-1} + \varepsilon_{i,t}$	$\beta_0 + \beta$	$^{\mathrm{CF}}CF_{i,t-1}+\varepsilon_{i,t}$
Year	β^{Earn}	Adj. R ² _{EARN}	β^{CF}	Adj. R ² _{CF}
	(1)	(2)	(3)	(4)
1989	0.38	0.07	0.24	0.04
1990	0.54	0.15	0.28	0.07
1991	0.56	0.19	0.32	0.09
1992	0.52	0.19	0.39	0.12
1993	0.61	0.19	0.42	0.11
1994	0.53	0.19	0.40	0.12
1995	0.48	0.15	0.41	0.13
1996	0.59	0.19	0.40	0.11
1997	0.64	0.26	0.46	0.17
1998	0.49	0.16	0.40	0.12
1999	0.54	0.20	0.41	0.13
2000	0.65	0.02	0.46	0.01
2001	0.62	0.20	0.43	0.10
2002	0.68	0.32	0.59	0.25
2003	0.56	0.31	0.43	0.23
2004	0.71	0.32	0.57	0.25
2005	0.69	0.34	0.56	0.27
2006	0.70	0.32	0.59	0.27
2007	0.75	0.38	0.59	0.28
2008	0.76	0.27	0.54	0.16
2009	0.45	0.24	0.39	0.18
2010	0.53	0.22	0.38	0.14
2011	0.69	0.32	0.57	0.26
2012	0.75	0.34	0.62	0.26
2013	0.70	0.33	0.62	0.27
2014	0.78	0.43	0.65	0.35
2015	0.75	0.32	0.65	0.25
Average		0.24		0.17
Trend (t-value)		0.0089*** [5.44]		0.0084*** [6.21]

Panel B: Cash flow predictability using lagged earnings and lagged cash flows: Cash flows estimated using balance sheet

Table 5 presents results of regressions, estimated annually, of current operating cash flows on lagged earnings and cash flows for the period 1989-2015. In Panel A (B), cash flows are computed using the cash flow statement (balance sheet) approach.

 β^{EARN} and Adj. R^{2}_{EARN} are the coefficient estimate and explanatory power, respectively, of the following regression model estimated by year:

$$CF_{i,t} = \beta_0 + \beta^{\text{EARN}} EARN_{i,t-1} + \varepsilon_{i,t}$$

 β^{CF} and Adj. R^2_{CF} are the coefficient estimate and explanatory power, respectively, of the following regression model estimated by year:

$$CF_{i,t} = \beta_0 + \beta^{CF} CF_{i,t-1} + \varepsilon_{i,t}$$

Trend is the coefficient estimate obtained by regressing yearly estimates ((β /Adj. R²)) obtained from each specification above on the time variable. *Average* is average explanatory power over the sample period. All other variables are described in Table 2. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels (two-tailed p-values), respectively.

Year	Adj. R ² _{CF,ACC}	Adj. R ² _{CF}	Adj. R ² _{ACC}	Inc. R ² : CF	Inc. R ² : ACC
	(1)	(2)	(3)	(4)	(5)
1989	0.29	0.28	0.07	0.22	0.02
1990	0.26	0.24	0.03	0.23	0.02
1991	0.25	0.23	0.02	0.23	0.02
1992	0.27	0.26	0.03	0.23	0.01
1993	0.29	0.28	0.04	0.25	0.01
1994	0.32	0.30	0.02	0.30	0.02
1995	0.29	0.28	0.04	0.25	0.01
1996	0.28	0.25	0.01	0.27	0.03
1997	0.36	0.33	0.01	0.35	0.03
1998	0.36	0.35	0.01	0.35	0.01
1999	0.35	0.33	0.00	0.35	0.02
2000	0.32	0.29	0.00	0.32	0.03
2001	0.33	0.31	0.00	0.33	0.02
2002	0.39	0.37	0.01	0.39	0.02
2003	0.43	0.41	0.00	0.43	0.02
2004	0.49	0.48	0.01	0.48	0.01
2005	0.45	0.43	0.01	0.44	0.02
2006	0.49	0.47	0.00	0.49	0.02
2007	0.44	0.41	0.00	0.44	0.03
2008	0.40	0.38	0.01	0.39	0.02
2009	0.35	0.33	0.00	0.34	0.02
2010	0.39	0.37	0.00	0.38	0.02
2011	0.40	0.38	0.00	0.40	0.02
2012	0.52	0.50	0.01	0.51	0.02
2013	0.48	0.47	0.00	0.48	0.02
2014	0.55	0.53	0.00	0.55	0.02
2015	0.53	0.51	0.00	0.53	0.01
Average	0.38	0.36	0.01	0.37	0.02
Trend	0.0098***	0.0096***	-0.0016***	0.0114***	0.0000
(t-value)	[8.47]	[8.32]	[-5.40]	[9.98]	[0.84]

Table 6: Cash flow predictability over time: Incremental predictive ability

Table 6 presents the incremental predictive ability of cash flows and accruals in predicting future cash flows for the sample period 1989-2015.

Adj. $R^{2}_{CF,ACC}$ is the explanatory power of the following regression model estimated by year:

$$CF_{i,t} = \beta_0 + \beta_1^{ACC} ACC_{i,t-1} + \beta_1^{CF} CF_{i,t-1} + \varepsilon_{i,t-1}$$

Adj. R^2_{CF} is the explanatory power of the following regression model estimated by year:

$$CF_{i,t} = \beta_0 + \beta^{CF} CF_{i,t-1} + \varepsilon_{i,t}$$

Adj. R^{2}_{ACC} is the explanatory power of the following regression model estimated by year:

 $CF_{i,t} = \beta_0 + \beta^{ACC} ACC_{i,t-1} + \varepsilon_{i,t}$

Inc. R²: ACC (measured as Adj. $R^{2}_{CF,ACC}$ - Adj. R^{2}_{CF}) and Inc. R²: CF (measured as Adj. $R^{2}_{CF,ACC}$ - Adj. R^{2}_{ACC}) refer to the incremental explanatory power of accruals and cash flows, respectively. *Trend* is the coefficient estimate obtained by regressing yearly estimates (Adj. R^{2} / Inc. R^{2}) obtained from each specification above on the time variable. *Average* is average explanatory power over the sample period. All other variables are described in Table 2. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels (two-tailed p-values), respectively.

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Year	Adj. R ² _{ACC_COMP}	Adj. R^2_{CF, ACC_COMP}	Inc. R ² : ACC_COMP	Inc. R ² : CF
	(1)	(2)	(3)	(4)
1989	0.14	0.33	0.05	0.19
1990	0.09	0.32	0.08	0.23
1991	0.07	0.29	0.06	0.22
1992	0.11	0.33	0.07	0.22
1993	0.09	0.33	0.06	0.24
1994	0.09	0.36	0.06	0.27
1995	0.08	0.32	0.03	0.24
1996	0.04	0.29	0.04	0.25
1997	0.03	0.37	0.05	0.34
1998	0.03	0.37	0.02	0.34
1999	0.01	0.36	0.04	0.35
2000	0.03	0.34	0.05	0.31
2001	0.05	0.35	0.04	0.30
2002	0.05	0.43	0.06	0.37
2003	0.04	0.47	0.07	0.43
2004	0.05	0.51	0.03	0.46
2005	0.04	0.47	0.04	0.43
2006	0.05	0.51	0.04	0.46
2007	0.04	0.46	0.06	0.43
2008	0.07	0.44	0.07	0.37
2009	0.05	0.38	0.05	0.33
2010	0.05	0.42	0.05	0.37
2011	0.04	0.42	0.04	0.37
2012	0.05	0.55	0.05	0.51
2013	0.03	0.50	0.04	0.48
2014	0.03	0.57	0.04	0.54
2015	0.03	0.54	0.02	0.51
Average	0.05	0.41	0.05	0.35
Trend (t-value)	-0.0023*** [-4.13]	0.0090*** [8.01]	-0.0007** [-1.98]	0.0113*** [9.67]

Year	Adj. R² _{CF}	Adj. R ² CF, ACC_EST	Adj. R ² CF, ACC_DELTA	Adj. R ² _{CF,} acc_comp	Inc. R ² : ACC_EST	Inc. R ² : ACC_DELTA	Inc. R ² : ACC_COMP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1989	0.27	0.27	0.30	0.31	0.00	0.03	0.03
1990	0.24	0.25	0.30	0.30	0.00	0.06	0.06
1991	0.23	0.23	0.28	0.28	0.00	0.05	0.05
1992	0.26	0.26	0.30	0.30	0.00	0.04	0.04
1993	0.28	0.28	0.31	0.31	0.00	0.03	0.03
1994	0.32	0.32	0.35	0.36	0.00	0.04	0.04
1995	0.29	0.29	0.32	0.32	0.00	0.03	0.03
1996	0.25	0.25	0.28	0.29	0.00	0.03	0.04
1997	0.33	0.33	0.36	0.37	0.00	0.04	0.05
1998	0.35	0.35	0.37	0.38	0.00	0.03	0.03
1999	0.33	0.33	0.36	0.36	0.00	0.03	0.04
2000	0.29	0.29	0.34	0.34	0.00	0.05	0.05
2001	0.31	0.31	0.37	0.37	0.00	0.06	0.06
2002	0.37	0.37	0.43	0.43	0.00	0.06	0.06
2003	0.41	0.41	0.45	0.46	0.00	0.05	0.05
2004	0.48	0.48	0.52	0.52	0.00	0.03	0.04
2005	0.43	0.43	0.46	0.47	0.00	0.03	0.04
2006	0.47	0.47	0.50	0.51	0.00	0.04	0.04
2007	0.41	0.41	0.45	0.46	0.00	0.05	0.06
2008	0.38	0.38	0.44	0.44	0.00	0.06	0.06
2009	0.33	0.33	0.37	0.37	0.00	0.04	0.05
2010	0.37	0.37	0.43	0.43	0.00	0.06	0.07
2011	0.38	0.38	0.41	0.42	0.00	0.03	0.04
2012	0.50	0.50	0.53	0.54	0.00	0.03	0.04
2013	0.47	0.47	0.50	0.50	0.00	0.03	0.03
2014	0.53	0.53	0.56	0.57	0.00	0.03	0.04
2015	0.51	0.51	0.53	0.54	0.00	0.03	0.03
Average	0.36	0.36	0.40	0.41	0.00	0.04	0.04
Trend	0.01***	0.01***	0.01***	0.01***	0.00	-0.00	0.00
(t-value)	[8.20]	[8.22]	[8.75]	[8.85]	[0.24]	[-0.26]	[0.14]

Panel B: Disaggregating accruals based on magnitude of managerial estimates

Table 7 reports the explanatory power of the regression, estimated annually, of current operating cash flows on lagged accrual components and lagged cash flows for the period 1989-2015.

Panel A reports the estimation results after decomposing accruals into its major components as in Barth et al. (2001).

Adj. R²_{ACC_COMP} (Adj. R²_{CF,ACC_COMP}) is the explanatory power of the following regression model after excluding

(including) current cash flows as an explanatory variable, estimated by year: $CF_{i,t} = \beta_0 + \beta^{CHG_AR} CHG_AR_{i,t-1} + \beta^{CHG_INV} CHG_INV_{i,t-1} + \beta^{CHG_AP} CHG_AP_{i,t-1} + \beta^{DEPR} DEPR_{i,t-1} + \beta^{AMORT} AMORT_{i,t-1} + \beta^{OTHER} OTHER_{i,t-1} + \beta^{CF} CF_{i,t-1+\varepsilon_{i,t}}$

Inc.R²: ACC_COMP (measured as Adj. R²_{CF, ACC_COMP} - Adj. R²_{CF}) refers to the incremental explanatory power of lagged accrual components for predicting current cash flows. Inc. R²: CF (measured as Adj. R²_{CF, ACC_COMP} - Adj. R²_{ACC_COMP}) refers to the incremental explanatory power of lagged cash flows for predicting current cash flows. *Trend* is the coefficient estimate obtained by regressing yearly estimates (Adj. R²/ Inc. R²) obtained from the specification above on the time variable. *Average* is average explanatory power over the sample period. All other variables are described in Table 2. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels (two-tailed p-values), respectively.

Panel B reports the estimation results after decomposing accruals into components as in Lev et al. (2010).

Adj. $R^{2}_{ACC_EST}$ (Adj. R^{2}_{CF,ACC_EST}) is the explanatory power of the following regression model after excluding (including) current cash flows as an explanatory variable, estimated by year: $CF_{i,t} = \beta_0 + \beta^{ACC_EST} ACC_EST_{i,t-1} + \beta^{CF} CF_{i,t-1+} \varepsilon_{i,t}$

Adj. $R^{2}_{ACC_DELTA}$ (Adj. R^{2}_{CF,ACC_DELTA}) is the explanatory power of the following regression model after excluding (including) current cash flows as an explanatory variable, estimated by year: $CF_{i,t} = \beta_0 + \beta^{ACC_DELTA} ACC_DELTA_{i,t-1} + \beta^{CF} CF_{i,t-1+} \varepsilon_{i,t}$

Adj. $R^{2}_{ACC_COMP}$ (Adj. R^{2}_{CF,ACC_COMP}) is the explanatory power of the following regression model after excluding (including) current cash flows as an explanatory variable, estimated by year: $CF_{i,t} = \beta_0 + \beta^{ACC_EST} ACC_EST_{i,t-1} + \beta^{ACC_DELTA} ACC_DELTA_{i,t-1} + \beta^{CF} CF_{i,t-1} + \varepsilon_{i,t}$

Inc.R²: ACC_EST (measured as Adj. R^{2}_{CF, ACC_EST} - Adj. R^{2}_{CF}) refers to the incremental explanatory power of lagged accruals affected by managerial estimates for predicting current cash flows. Inc.R²: ACC_DELTA (measured as Adj. R^{2}_{CF, ACC_DELTA} - Adj. R^{2}_{CF}) refers to the incremental explanatory power of lagged accruals unaffected by managerial estimates for predicting current cash flows. Inc.R²: ACC_COMP (measured as Adj. R^{2}_{CF, ACC_COMP} - Adj. R^{2}_{CF}) refers to the incremental explanatory power of lagged accruals unaffected by managerial estimates for predicting current cash flows. Inc.R²: ACC_COMP (measured as Adj. R^{2}_{CF, ACC_COMP} - Adj. R^{2}_{CF}) refers to the incremental explanatory power of lagged accrual components for predicting current cash flows. Inc. R²: CF (measured as Adj. R^{2}_{CF, ACC_COMP} - Adj. $R^{2}_{ACC_COMP}$) refers to the incremental explanatory power of lagged cash flows for predicting current cash flows. *Trend* is the coefficient estimate obtained by regressing yearly estimates (Adj. R^{2} / Inc. R^{2}) obtained from the specification above on the time variable. *Average* is average explanatory power over the sample period. All other variables are described in Table 2. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels (two-tailed p-values), respectively.

Panel A: Desc	Panel A: Descriptive statistics											
Variables	Ν	Mean	SD	P25	Median	P75	Min	Max				
OperCyc	27	114.685	5.133	109.648	115.534	118.842	106.998	123.762				
WorkCap	27	0.056	0.036	0.028	0.032	0.100	0.013	0.113				
SG&A	27	0.230	0.012	0.221	0.229	0.242	0.208	0.247				

Table 8: Determinants of the time-series patterns in cash flow prediction ability

Panel B: Determinants – time trends

	OperCyc	WorkCap	SG&A	
Time	-0.466*** [-5.19]	-0.004*** [-12.01]	0.001** [2.33]	
Intercept	121.200*** [84.32]	0.115*** [20.39]	0.221*** [52.10]	
Adj. R ²	0.50	0.85	0.15	

		$R^2_{CF,t} = \beta_0$	+ β_1 * Tim	$e + \beta_2 * Oper$	$Cyc + \beta_3 * Wo$	rkCap + β_4^*	$SG\&A + \varepsilon_t$	
_		Adj. R ²	CF		Inc. R ² : CF			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OperCyc	-0.013*** [-5.13]			-0.005* [-1.95]	-0.015*** [-4.54]			-0.004* [-1.87]
WorkCap		-1.976*** [-5.89]		0.024 [0.04]		-2.386*** [-6.97]		0.182 [0.31]
SG&A			3.378* [1.94]	0.735 [0.662]			4.643** [2.50]	1.816* [1.74]
Time				0.007* [1.93]				0.009*** [2.64]
Intercept	1.875*** [6.26]	0.471*** [15.26]	-0.416 [-1.03]	0.678* [1.80]	2.057*** [5.56]	0.500*** [17.23]	-0.700 [-1.63]	0.295 [0.84]
Adj. R ²	0.56	0.63	0.16	0.74	0.55	0.73	0.26	0.83

Panel C: Determinants of current cash flows' ability to predict future cash flows

Table 8 reports results on the determinants of trends observed in the cash flow predictive ability of current cash flows.

The sample spans 27 years from 1989-2015. All variables are described in Table 2. All continuous variables are winsorized at the 1 percent and 99 percent levels. Panel A provides descriptive statistics of the determinant variables. Panel B presents time trends in the determinant variables. Panel C provides OLS regression estimates of the determinants of cash flows' ability to predict future cash flows. The t-statistics in parentheses are adjusted for Newey–West autocorrelations of three lags. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels (two-tailed p-values), respectively.

Adj. R^{2}_{CF} is the explanatory power of the following regression model estimated by year:

$$CF_{i,t} = \beta_0 + \beta^{CF} CF_{i,t-1} + \varepsilon_{i,t}$$

Inc. R²: CF refers to the incremental explanatory power of cash flows (measured as Adj. R²_{ACC,CF} - Adj. R²_{ACC}).

$CF_{i,t} =$	$\beta_0 + \beta^{\text{EARN}} EARN_{i,t-1} + \varepsilon_{i,t}$					$\beta_{0} + \beta^{\text{CF}} CF_{i,t-1} + \varepsilon_{i,t}$			
		Adj. R	² EARN			Adj.	$R^2 CF$		
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	
1990	0.09	0.12	0.08	0.08	0.03	0.05	0.04	0.01	
1991	0.12	0.14	0.23	0.16	0.03	0.07	0.10	0.03	
1992	0.14	0.24	0.18	0.06	0.05	0.15	0.10	0.01	
1993	0.16	0.26	0.25	0.12	0.08	0.17	0.15	0.07	
1994	0.11	0.11	0.19	0.16	0.06	0.04	0.11	0.07	
1995	0.11	0.20	0.23	0.13	0.06	0.14	0.15	0.07	
1996	0.21	0.30	0.28	0.20	0.11	0.20	0.17	0.11	
1997	0.15	0.29	0.16	0.16	0.11	0.20	0.10	0.10	
1998	0.25	0.17	0.33	0.21	0.14	0.10	0.24	0.12	
1999	0.24	0.29	0.21	0.18	0.08	0.25	0.20	0.11	
2000	0.14	0.21	0.23	0.19	0.07	0.20	0.15	0.10	
2001	0.15	0.20	0.27	0.16	0.14	0.16	0.21	0.11	
2002	0.19	0.12	0.25	0.21	0.10	0.06	0.13	0.12	
2003	0.13	0.20	0.23	0.19	0.06	0.12	0.17	0.10	
2004	0.20	0.27	0.24	0.20	0.08	0.19	0.16	0.11	
2005	0.17	0.36	0.18	0.10	0.11	0.22	0.14	0.05	
2006	0.16	0.26	0.19	0.19	0.10	0.16	0.14	0.08	
2007	0.10	0.23	0.17	0.21	0.07	0.18	0.14	0.14	
2008	0.18	0.33	0.19	0.05	0.11	0.21	0.16	0.04	
2009	0.11	0.45	0.08	0.12	0.10	0.27	0.14	0.06	
2010	0.20	0.16	0.12	0.21	0.13	0.09	0.10	0.14	
2011	0.25	0.18	0.33	0.32	0.16	0.13	0.35	0.26	
2012	0.38	0.31	0.17	0.27	0.31	0.17	0.16	0.21	
2013	0.27	0.32	0.27	0.16	0.28	0.29	0.29	0.15	
2014	0.32	0.19	0.26	0.22	0.33	0.16	0.21	0.19	
2015	0.33	0.35	0.22	0.24	0.21	0.29	0.19	0.20	
Average	0.19	0.24	0.21	0.17	0.12	0.16	0.16	0.11	
Trend	0.01***	0.00**	0.00	0.00***	0.01***	0.00***	0.00***	0.01***	
t-value	[4.16]	[2.27]	[0.14]	[2.81]	[5.39]	[2.81]	[2.97]	[4.78]	

 Table 9: Cash flow predictability over time: Quarterly frequency

Table 9 reports the explanatory power of regressions estimated quarterly, of current operating cash flows on lagged earnings and cash flows for the period 1990-2015.

Adj. R^{2}_{EARN} is the explanatory power of the following regression model estimated by quarter:

 $CF_{i,t} = \beta_0 + \beta^{\text{EARN}} EARN_{i,t-1} + \varepsilon_{i,t}$ Adj. R²_{CF} is the explanatory power of the following regression model estimated by quarter: $CF_{i,t} = \beta_0 + \beta^{\text{CF}} CF_{i,t-1} + \varepsilon_{i,t}$

Trend is the coefficient estimate obtained by regressing quarterly explanatory power (Adj. R^2) obtained from each specification above on the time variable. *Average* is average explanatory power over quarters. All other variables are described in Table 2. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels (two-tailed p-values), respectively.

Year		Adj.	Adj.	Adj.	Adj.	Inc. R ² :	Inc. R ² :
	$\beta^{(CF-ACC)}$	\mathbb{R}^2 (CF- ACC)	R ² EARN	$R^{2}CF$	R^{2} CF,ACC	ACC	CF
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1998	-0.34	0.09	0.20	0.26	0.30	0.04	0.29
1999	-0.27	0.06	0.20	0.31	0.33	0.03	0.33
2000	-0.27	0.07	0.24	0.33	0.37	0.04	0.36
2001	-0.06	0.00	0.32	0.38	0.42	0.04	0.42
2002	-0.12	0.01	0.33	0.41	0.44	0.03	0.43
2003	-0.13	0.02	0.31	0.41	0.43	0.02	0.43
2004	-0.21	0.07	0.35	0.44	0.47	0.03	0.47
2005	-0.23	0.08	0.35	0.40	0.44	0.04	0.44
2006	-0.17	0.04	0.40	0.44	0.48	0.05	0.48
2007	-0.16	0.04	0.43	0.46	0.51	0.05	0.50
2008	-0.09	0.01	0.40	0.47	0.50	0.04	0.50
2009	0.04	0.00	0.44	0.46	0.51	0.06	0.48
2010	-0.03	0.00	0.44	0.49	0.53	0.04	0.49
2011	-0.06	0.00	0.44	0.49	0.52	0.04	0.50
2012	-0.05	0.00	0.47	0.50	0.55	0.05	0.52
2013	0.00	0.00	0.50	0.53	0.58	0.05	0.55
2014	0.11	0.01	0.47	0.52	0.56	0.05	0.52
2015	0.11	0.01	0.51	0.57	0.61	0.05	0.54
Average	-0.11	0.03	0.38	0.44	0.48	0.04	0.46
Trend (t-value)	0.0205*** [6.45]	-0.0038*** [-3.52]	0.0174*** [14.11]	0.0144*** [12.85]	0.0152*** [14.19]	0.0009*** [2.63]	0.0125*** [9.86]

 Table 10: Accrual-cash flow relation and cash flow predictability over time: International sample firms

Table 10 presents the correlation between accruals and cash flows, and the operating cash flow predictability of earnings and cash flows for the period 1998-2015 using a sample of international firms from 21 jurisdictions. The sample comprises of 139,707 observations based on annual data corresponding to the following jurisdictions: Australia, Brazil, Germany, Denmark, France, UK, Hong Kong, Indonesia, India, Israel, Italy, Korea, Malaysia, The Netherlands, Norway, Pakistan, Singapore, Sweden, Switzerland, Thailand, and South Africa.

 β (^{CF-ACC)} and Adj. R²_{CF-ACC} are the coefficient estimate and explanatory power, respectively, of the following regression model estimated by year:

$$ACC_{i,t} = \beta_0 + \beta^{(\text{CF-ACC})}CF_{i,t} + \varepsilon_{i,t}$$

Adj. R²_{EARN} is the explanatory power of the following regression model estimated by year:

$$CF_{i,t} = \beta_0 + \beta^{\text{EARN}} EARN_{i,t-1} + \varepsilon_{i,t}$$

Adj. R²_{CF} is the explanatory power of the following regression model estimated by year:

$$CF_{i,t} = \beta_0 + \beta^{CF} CF_{i,t-1} + \varepsilon_{i,t},$$

Adj. $R^{2}_{CF,ACC}$ is the explanatory power of the following regression model estimated by year:

 $CF_{i,t} = \beta_{\theta} + \beta_1^{ACC} ACC_{i,t-1} + \beta_1^{CF} CF_{i,t-1} + \varepsilon_{i,t},$

Inc. R²: ACC and Inc. R²: CF refer to the incremental explanatory power of accruals and cash flows respectively. *Trend* is the coefficient estimate obtained by regressing yearly estimates ((β /Adj. R²)) obtained from each specification above on the time variable. *Average* is average explanatory power over the sample period. All other variables are described in Table 2. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels (two-tailed p-values), respectively.

Appendix Tables

Table A1: Alternative definitions of earnings, cash flows, and accruals: Cash flow predictability over time

Definition	Earnings	Cash Flows	Accruals	Are Cash Flows better predictors than Earnings?
1	IB	OANCF	IB-OANCF	Yes
2	IB	OANCF+INTPN	IB-(OANCF+INTPN)	Yes
3	IBC	OANCF-DPC	IBC-(OANCF-DPC)	Yes
4	IBC	OANCF-XIDOC	IBC-(OANCF- XIDOC)	Yes
5	IBC	OANCF	IBC-OANCF	Yes
6	NI	OANCF-DP	NI-(OANCF-DP)	Yes
7	NI	OANCF	NI-OANCF	Yes
8	PI	OANCF-XIDOC- TXPD	PI-(OANCF-XIDOC- TXPD)	Yes

Table A1.	Panel A: Summar	v of alternate definitions	of earnings.	cash flows	and accrual
					,

Table A1, Panel A provides alternate definitions of earnings, cash flows, and accruals computed using the following Compustat variables: Income before extraordinary items (IB); Income before extraordinary items – Cash Flow Statement (IBC); Net Income (NI); Pretax Income (PI); Operating Activities – Net Cash Flow (OANCF); Interest Paid – Net (INTPN); Depreciation and Amortization – Cash Flow Statement (DPC); Depreciation and Amortization (DP); Extraordinary items and discontinued operations – Cash Flow Statement (XIDOC); Income Taxes Paid (TXPD).

Table A1 Panels B through I present results of regressions, estimated annually, of current operating cash flows on lagged earnings, accruals, and cash flows for the period 1989-2015, using variables as defined in Definition #1 through #8 of Table A1 Panel A, respectively.

 β^{EARN} and Adj. R^{2}_{EARN} are the coefficient estimate and explanatory power, respectively, of the following regression model estimated by year:

$$CF_{i,t} = \beta_0 + \beta^{\text{EARN}} EARN_{i,t-1} + \varepsilon_{i,t}$$

 β^{CF} and Adj. R^2_{CF} are the coefficient estimate and explanatory power, respectively, of the following regression model estimated by year:

$$CF_{i,t} = \beta_0 + \beta^{CF} CF_{i,t-1} + \varepsilon_{i,t}$$

 β^{ACC} and Adj. R^2_{ACC} are the coefficient estimate and explanatory power, respectively, of the following regression model estimated by year:

$$CF_{i,t} = \beta_0 + \beta^{ACC}ACC_{i,t-1} + \varepsilon_{i,t}$$

Trend is the coefficient estimate obtained by regressing yearly estimates ((β /Adj. R²)) obtained from each specification above on the time variable. *Average* is average explanatory power over the sample period. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels (two-tailed p-values), respectively.

$CF_{i,t} =$	$\beta_0 + \beta^{EAF}$	$e^{RN}EARN_{i,t-1} + \varepsilon_{i,t}$	$\beta_0 + \beta^0$	$CFCF_{i,t-1} + \varepsilon_{i,t}$	$\beta_0 + \beta^{AC}$	$CACC_{i,t-1} + \varepsilon_{i,t}$
Year	β^{EARN}	Adj. R ² _{EARN}	β^{CF}	Adj. R ² _{CF}	β^{ACC}	Adj. R ² _{ACC}
	(1)	(2)	(3)	(4)	(5)	(6)
1989	0.58	0.15	0.55	0.28	-0.31	0.07
1990	0.45	0.13	0.51	0.24	-0.22	0.04
1991	0.41	0.13	0.52	0.24	-0.18	0.03
1992	0.38	0.12	0.56	0.28	-0.21	0.04
1993	0.39	0.12	0.57	0.29	-0.21	0.04
1994	0.41	0.15	0.62	0.32	-0.16	0.02
1995	0.40	0.13	0.55	0.30	-0.23	0.05
1996	0.46	0.16	0.58	0.26	-0.13	0.01
1997	0.50	0.23	0.61	0.33	-0.10	0.01
1998	0.41	0.18	0.62	0.34	-0.13	0.01
1999	0.44	0.23	0.60	0.32	-0.03	0.00
2000	0.56	0.24	0.69	0.29	0.04	0.00
2001	0.39	0.22	0.58	0.30	0.05	0.00
2002	0.33	0.23	0.62	0.37	0.07	0.01
2003	0.45	0.29	0.68	0.39	0.06	0.00
2004	0.60	0.34	0.75	0.49	-0.17	0.01
2005	0.57	0.33	0.69	0.43	-0.10	0.01
2006	0.60	0.34	0.75	0.46	-0.08	0.00
2007	0.54	0.33	0.66	0.41	-0.03	0.00
2008	0.55	0.30	0.65	0.39	-0.10	0.01
2009	0.32	0.19	0.59	0.34	0.03	0.00
2010	0.44	0.24	0.64	0.37	-0.06	0.00
2011	0.54	0.28	0.71	0.39	-0.08	0.00
2012	0.64	0.36	0.79	0.51	-0.14	0.01
2013	0.54	0.31	0.78	0.48	-0.06	0.00
2014	0.63	0.42	0.80	0.54	-0.05	0.00
2015	0.54	0.37	0.73	0.51	0.00	0.00
Average		0.24		0.37		0.01
Trend		0.010***		0.010***		-0.002***
(t-value)		[8.49]		[8.11]		[-5.61]

 Table A1, Panel B: Cash flow predictability over time: Definition #1

$CF_{i,t} =$	$\beta_0 + \beta^{EAF}$	$ext{NEARN}_{i,t-1} + \varepsilon_{i,t}$	$\beta_0 + \beta^0$	$CFCF_{i,t-1} + \varepsilon_{i,t}$	$\beta_0 + \beta^{ACC}$	$ACC_{i,t-1} + \varepsilon_{i,t}$
Year	β^{EARN}	Adj. R ² _{EARN}	β^{CF}	Adj. R ² _{CF}	β^{ACC}	Adj. R ² _{ACC}
	(1)	(2)	(3)	(4)	(5)	(6)
1989	0.48	0.10	0.53	0.29	-0.34	0.10
1990	0.31	0.07	0.46	0.19	-0.22	0.04
1991	0.30	0.07	0.47	0.19	-0.18	0.03
1992	0.26	0.06	0.53	0.25	-0.24	0.06
1993	0.29	0.07	0.55	0.26	-0.25	0.06
1994	0.33	0.10	0.59	0.31	-0.20	0.04
1995	0.32	0.09	0.52	0.27	-0.25	0.06
1996	0.39	0.11	0.55	0.23	-0.16	0.02
1997	0.45	0.18	0.58	0.31	-0.15	0.02
1998	0.37	0.14	0.59	0.31	-0.16	0.02
1999	0.40	0.19	0.59	0.31	-0.06	0.00
2000	0.48	0.24	0.63	0.34	-0.08	0.00
2001	0.37	0.20	0.57	0.31	-0.02	0.00
2002	0.31	0.20	0.61	0.37	0.02	0.00
2003	0.42	0.25	0.66	0.38	0.00	0.00
2004	0.57	0.29	0.76	0.47	-0.22	0.03
2005	0.54	0.29	0.67	0.42	-0.12	0.01
2006	0.55	0.30	0.73	0.45	-0.13	0.01
2007	0.50	0.29	0.65	0.41	-0.06	0.00
2008	0.49	0.25	0.62	0.37	-0.13	0.01
2009	0.27	0.15	0.57	0.32	-0.01	0.00
2010	0.37	0.17	0.62	0.33	-0.10	0.01
2011	0.50	0.23	0.71	0.35	-0.11	0.01
2012	0.61	0.32	0.79	0.49	-0.15	0.01
2013	0.50	0.26	0.78	0.44	-0.11	0.01
2014	0.58	0.36	0.78	0.52	-0.07	0.00
2015	0.54	0.36	0.75	0.54	-0.04	0.00
Average		0.20		0.35		0.02
Trend		0.010***		0.010***		-0.002***
(t-value)		[7.97]		[7.64]		[-5.37]

 Table A1, Panel C: Cash flow predictability over time: Definition #2

$CF_{i,t} =$	$\beta_0 + \beta^{EAF}$	$ext{RN}EARN_{i,t-1} + \varepsilon_{i,t}$	$\beta_0 + \beta^0$	$CFCF_{i,t-1} + \varepsilon_{i,t}$	$\beta_0 + \beta^{ACC}$	$ACC_{i,t-1} + \varepsilon_{i,t}$
Year	β^{EARN}	Adj. R ² _{EARN}	β^{CF}	Adj. R ² _{CF}	β^{ACC}	Adj. R ² _{ACC}
	(1)	(2)	(3)	(4)	(5)	(6)
1989	0.60	0.18	0.52	0.25	-0.23	0.04
1990	0.48	0.16	0.47	0.20	-0.12	0.01
1991	0.45	0.15	0.49	0.19	-0.09	0.00
1992	0.43	0.16	0.52	0.23	-0.10	0.01
1993	0.43	0.15	0.54	0.24	-0.12	0.01
1994	0.47	0.20	0.59	0.28	-0.04	0.00
1995	0.45	0.18	0.53	0.26	-0.13	0.01
1996	0.53	0.19	0.57	0.23	-0.05	0.00
1997	0.56	0.28	0.62	0.32	-0.02	0.00
1998	0.48	0.23	0.62	0.32	-0.05	0.00
1999	0.51	0.28	0.61	0.33	0.03	0.00
2000	0.62	0.26	0.71	0.29	0.11	0.00
2001	0.48	0.29	0.60	0.32	0.14	0.01
2002	0.40	0.28	0.58	0.33	0.19	0.03
2003	0.49	0.35	0.64	0.38	0.17	0.02
2004	0.65	0.40	0.73	0.46	-0.05	0.00
2005	0.62	0.37	0.70	0.41	0.03	0.00
2006	0.63	0.39	0.74	0.45	0.03	0.00
2007	0.57	0.36	0.64	0.39	0.09	0.00
2008	0.58	0.35	0.64	0.37	0.02	0.00
2009	0.35	0.23	0.59	0.32	0.10	0.01
2010	0.47	0.29	0.62	0.35	0.04	0.00
2011	0.57	0.33	0.69	0.36	0.06	0.00
2012	0.65	0.40	0.78	0.48	0.01	0.00
2013	0.57	0.35	0.78	0.46	0.05	0.00
2014	0.66	0.46	0.79	0.53	0.07	0.00
2015	0.56	0.39	0.73	0.49	0.09	0.00
Average		0.28		0.34		0.01
Trend		0.010***		0.010***		-0.000**
(t-value)		[8.14]		[9.22]		[-2.05]

 Table A1, Panel D: Cash flow predictability over time: Definition #3

$CF_{i,t} =$	$\beta_0 + \beta^{EAB}$	$EARN_{i,t-1} + \varepsilon_{i,t}$	$\beta_0 + \beta^0$	$CFCF_{i,t-1} + \varepsilon_{i,t}$	$\beta_0 + \beta^{ACC}$	$ACC_{i,t-1} + \varepsilon_{i,t}$
Year	β^{EARN}	Adj. R ² _{EARN}	β^{CF}	Adj. R ² _{CF}	β^{ACC}	Adj. R ² _{ACC}
	(1)	(2)	(3)	(4)	(5)	(6)
1989	0.54	0.14	0.53	0.28	-0.30	0.07
1990	0.45	0.14	0.51	0.24	-0.21	0.03
1991	0.42	0.13	0.52	0.23	-0.17	0.02
1992	0.37	0.11	0.54	0.26	-0.20	0.04
1993	0.39	0.12	0.56	0.28	-0.21	0.04
1994	0.41	0.15	0.61	0.32	-0.16	0.02
1995	0.39	0.13	0.54	0.29	-0.22	0.04
1996	0.46	0.16	0.57	0.25	-0.12	0.01
1997	0.49	0.23	0.61	0.33	-0.09	0.01
1998	0.41	0.18	0.62	0.35	-0.13	0.01
1999	0.44	0.23	0.60	0.33	-0.03	0.00
2000	0.56	0.23	0.69	0.29	0.04	0.00
2001	0.38	0.22	0.58	0.31	0.05	0.00
2002	0.33	0.22	0.63	0.37	0.07	0.01
2003	0.45	0.31	0.67	0.41	0.07	0.00
2004	0.60	0.34	0.75	0.48	-0.17	0.01
2005	0.56	0.32	0.69	0.43	-0.10	0.01
2006	0.60	0.34	0.75	0.47	-0.10	0.00
2007	0.54	0.32	0.65	0.41	-0.03	0.00
2008	0.53	0.29	0.64	0.38	-0.10	0.01
2009	0.31	0.19	0.58	0.33	0.03	0.00
2010	0.44	0.24	0.64	0.37	-0.05	0.00
2011	0.54	0.28	0.71	0.38	-0.06	0.00
2012	0.63	0.36	0.79	0.50	-0.13	0.01
2013	0.54	0.31	0.79	0.47	-0.05	0.00
2014	0.62	0.42	0.79	0.53	-0.03	0.00
2015	0.53	0.37	0.73	0.53	0.01	0.00
Average		0.24		0.36		0.01
Trend		0.010***		0.010***		-0.002***
(t-value)		[8.40]		[8.21]		[-5.55]

Table A1, Panel E: Cash flow predictability over time: Definition #4

$CF_{i,t} =$	$\beta_0 + \beta^{EAF}$	$e^{RN}EARN_{i,t-1} + \varepsilon_{i,t}$	$\beta_0 + \beta^0$	$CFCF_{i,t-1} + \varepsilon_{i,t}$	$\beta_0 + \beta^{AC}$	$CACC_{i,t-1} + \varepsilon_{i,t}$
Year	β^{Earn}	Adj. R ² _{EARN}	β^{CF}	Adj. R ² _{CF}	β^{ACC}	Adj. R ² _{ACC}
	(1)	(2)	(3)	(4)	(5)	(6)
1989	0.55	0.14	0.52	0.27	-0.29	0.07
1990	0.45	0.13	0.51	0.24	-0.22	0.04
1991	0.41	0.13	0.52	0.24	-0.18	0.03
1992	0.38	0.12	0.56	0.28	-0.21	0.04
1993	0.39	0.12	0.57	0.29	-0.21	0.04
1994	0.42	0.15	0.62	0.32	-0.16	0.02
1995	0.40	0.13	0.55	0.30	-0.23	0.05
1996	0.46	0.16	0.58	0.26	-0.13	0.01
1997	0.50	0.23	0.61	0.33	-0.10	0.01
1998	0.41	0.18	0.62	0.34	-0.13	0.01
1999	0.44	0.23	0.60	0.32	-0.03	0.00
2000	0.56	0.24	0.69	0.29	0.04	0.00
2001	0.39	0.22	0.58	0.30	0.05	0.00
2002	0.33	0.22	0.62	0.36	0.07	0.01
2003	0.45	0.29	0.68	0.39	0.06	0.00
2004	0.61	0.34	0.75	0.49	-0.17	0.01
2005	0.57	0.33	0.69	0.43	-0.10	0.01
2006	0.60	0.34	0.75	0.46	-0.09	0.00
2007	0.54	0.33	0.66	0.41	-0.02	0.00
2008	0.54	0.30	0.65	0.38	-0.09	0.00
2009	0.32	0.19	0.59	0.34	0.03	0.00
2010	0.44	0.24	0.64	0.37	-0.05	0.00
2011	0.54	0.28	0.71	0.38	-0.07	0.00
2012	0.63	0.36	0.79	0.51	-0.13	0.01
2013	0.54	0.31	0.78	0.47	-0.05	0.00
2014	0.62	0.42	0.80	0.54	-0.03	0.00
2015	0.54	0.37	0.73	0.51	0.01	0.00
Average		0.24		0.36		0.01
Trend		0.010***		0.010***		-0.002***
(t-value)		[8.61]		[8.18]		[-5.89]

Table A1, Panel F: Cash flow predictability over time: Definition #5

$CF_{i,t} =$	$\beta_0 + \beta^{EAF}$	$e^{RN}EARN_{i,t-1} + \varepsilon_{i,t}$	$\beta_0 + \beta^0$	$CFCF_{i,t-1} + \varepsilon_{i,t}$	$\beta_0 + \beta^{ACC}$	$ACC_{i,t-1} + \varepsilon_{i,t}$
Year	β^{EARN}	Adj. R ² _{EARN}	β^{CF}	Adj. R ² _{CF}	β^{ACC}	Adj. R ² _{ACC}
	(1)	(2)	(3)	(4)	(5)	(6)
1989	0.43	0.13	0.52	0.25	-0.18	0.03
1990	0.44	0.16	0.46	0.20	-0.09	0.01
1991	0.40	0.14	0.48	0.18	-0.06	0.00
1992	0.38	0.14	0.52	0.23	-0.08	0.01
1993	0.36	0.13	0.53	0.23	-0.10	0.01
1994	0.41	0.17	0.58	0.28	-0.04	0.00
1995	0.39	0.15	0.53	0.26	-0.13	0.01
1996	0.48	0.18	0.56	0.23	-0.03	0.00
1997	0.52	0.26	0.62	0.32	-0.02	0.00
1998	0.43	0.20	0.61	0.32	-0.05	0.00
1999	0.48	0.26	0.60	0.31	0.05	0.00
2000	0.58	0.25	0.69	0.27	0.13	0.01
2001	0.45	0.28	0.59	0.31	0.16	0.02
2002	0.37	0.28	0.58	0.34	0.17	0.03
2003	0.43	0.32	0.65	0.38	0.15	0.02
2004	0.60	0.38	0.73	0.46	-0.01	0.00
2005	0.59	0.37	0.68	0.41	0.03	0.00
2006	0.60	0.37	0.73	0.43	0.05	0.00
2007	0.53	0.34	0.65	0.39	0.07	0.00
2008	0.55	0.33	0.64	0.36	0.02	0.00
2009	0.33	0.22	0.58	0.31	0.10	0.01
2010	0.45	0.27	0.62	0.34	0.03	0.00
2011	0.55	0.31	0.69	0.35	0.05	0.00
2012	0.64	0.38	0.78	0.48	0.00	0.00
2013	0.55	0.34	0.78	0.46	0.04	0.00
2014	0.64	0.45	0.79	0.52	0.07	0.00
2015	0.54	0.38	0.73	0.50	0.08	0.00
Average		0.27		0.34		0.01
Trend		0.010***		0.010***		-0.000
(t-value)		[8.67]		[8.80]		[-1.58]

 Table A1, Panel G: Cash flow predictability over time: Definition #6

$CF_{i,t} =$	$\beta_0 + \beta^{EAF}$	$RNEARN_{i,t-1} + \varepsilon_{i,t}$	$\beta_0 + \beta^{\text{CF}} CF_{i,t-1} + \varepsilon_{i,t}$		$\beta_0 + \beta^{ACC}$	$ACC_{i,t-1} + \varepsilon_{i,t}$
Year	β^{EARN}	Adj. R ² _{EARN}	β^{CF}	Adj. R ² _{CF}	β^{ACC}	Adj. R ² _{ACC}
	(1)	(2)	(3)	(4)	(5)	(6)
1989	0.43	0.12	0.55	0.28	-0.27	0.06
1990	0.41	0.12	0.51	0.24	-0.21	0.04
1991	0.37	0.11	0.52	0.24	-0.18	0.03
1992	0.34	0.11	0.56	0.28	-0.20	0.04
1993	0.34	0.10	0.57	0.29	-0.19	0.03
1994	0.37	0.14	0.62	0.32	-0.15	0.02
1995	0.35	0.11	0.55	0.30	-0.22	0.05
1996	0.44	0.15	0.58	0.26	-0.11	0.01
1997	0.48	0.22	0.61	0.33	-0.09	0.01
1998	0.39	0.17	0.62	0.34	-0.13	0.01
1999	0.43	0.22	0.60	0.32	-0.03	0.00
2000	0.54	0.23	0.69	0.29	0.04	0.00
2001	0.37	0.21	0.58	0.30	0.06	0.00
2002	0.32	0.22	0.62	0.37	0.07	0.01
2003	0.40	0.27	0.68	0.39	0.07	0.00
2004	0.57	0.33	0.75	0.49	-0.14	0.01
2005	0.56	0.32	0.69	0.43	-0.10	0.01
2006	0.58	0.33	0.75	0.46	-0.09	0.00
2007	0.51	0.31	0.66	0.41	-0.04	0.00
2008	0.53	0.29	0.65	0.39	-0.11	0.01
2009	0.31	0.18	0.59	0.34	0.03	0.00
2010	0.42	0.23	0.64	0.37	-0.07	0.00
2011	0.52	0.27	0.71	0.39	-0.08	0.00
2012	0.61	0.34	0.79	0.51	-0.14	0.01
2013	0.53	0.30	0.78	0.48	-0.07	0.00
2014	0.61	0.40	0.80	0.54	-0.05	0.00
2015	0.52	0.36	0.73	0.51	-0.02	0.00
Average		0.23		0.37		0.01
Trend		0.010***		0.010***		-0.002***
(t-value)		[8.74]		[8.11]		[-5.73]

 Table A1, Panel H: Cash flow predictability over time: Definition #7

$CF_{i,t} =$	$\beta_0 + \beta^{EAF}$	$ext{RN}EARN_{i,t-1} + \varepsilon_{i,t}$	$\beta_0 + \beta^{\text{CF}} CF_{i,t-1} + \varepsilon_{i,t}$		$\beta_0 + \beta^{ACC}$	$ACC_{i,t-1} + \varepsilon_{i,t}$
Year	β^{EARN}	Adj. R ² _{EARN}	β^{CF}	Adj. R ² _{CF}	β^{ACC}	Adj. R ² _{ACC}
	(1)	(2)	(3)	(4)	(5)	(6)
1989	0.21	0.05	0.47	0.21	-0.16	0.04
1990	0.12	0.02	0.38	0.13	-0.11	0.02
1991	0.15	0.03	0.38	0.13	-0.07	0.01
1992	0.11	0.02	0.44	0.16	-0.11	0.02
1993	0.12	0.02	0.46	0.19	-0.13	0.03
1994	0.13	0.03	0.50	0.21	-0.12	0.02
1995	0.12	0.02	0.43	0.18	-0.15	0.04
1996	0.17	0.04	0.43	0.14	-0.07	0.01
1997	0.26	0.09	0.49	0.20	-0.04	0.00
1998	0.19	0.06	0.49	0.22	-0.08	0.01
1999	0.21	0.07	0.47	0.20	-0.04	0.00
2000	0.31	0.11	0.56	0.20	-0.01	0.00
2001	0.23	0.10	0.43	0.17	0.02	0.00
2002	0.22	0.12	0.50	0.23	0.04	0.00
2003	0.29	0.18	0.54	0.26	0.08	0.01
2004	0.36	0.19	0.64	0.35	-0.03	0.00
2005	0.38	0.20	0.57	0.29	-0.01	0.00
2006	0.35	0.19	0.63	0.33	0.01	0.00
2007	0.32	0.17	0.53	0.26	0.03	0.00
2008	0.27	0.12	0.51	0.25	-0.05	0.00
2009	0.17	0.09	0.44	0.20	0.04	0.00
2010	0.22	0.10	0.51	0.22	0.00	0.00
2011	0.34	0.17	0.61	0.28	0.03	0.00
2012	0.37	0.20	0.64	0.35	-0.02	0.00
2013	0.38	0.22	0.71	0.37	0.05	0.00
2014	0.42	0.27	0.70	0.39	0.08	0.01
2015	0.36	0.25	0.66	0.39	0.07	0.01
Average		0.12		0.24		0.01
Trend		0.009***		0.008***		-0.001***
(t-value)		[9.06]		[6.84]		[-4.45]

 Table A1, Panel I: Cash flow predictability over time: Definition #8

Year	Adj. R ² _{CF}	Adj. R ² EAR1	Adj. R ² _{EAR2}	Adj. R ² EAR3	Adj. R ² _{SPI}
	(1)	(2)	(3)	(4)	(5)
1989	0.27	0.16	0.16	0.22	0.00
1990	0.24	0.17	0.16	0.25	0.00
1991	0.23	0.17	0.16	0.23	0.00
1992	0.26	0.15	0.14	0.22	0.00
1993	0.28	0.15	0.15	0.23	0.01
1994	0.32	0.17	0.17	0.23	0.01
1995	0.28	0.16	0.16	0.22	0.00
1996	0.25	0.18	0.19	0.24	0.01
1997	0.33	0.25	0.26	0.29	0.01
1998	0.35	0.23	0.23	0.28	0.01
1999	0.33	0.26	0.26	0.30	0.01
2000	0.29	0.25	0.26	0.29	0.00
2001	0.31	0.28	0.31	0.36	0.01
2002	0.37	0.32	0.33	0.41	0.03
2003	0.40	0.37	0.38	0.45	0.04
2004	0.48	0.40	0.40	0.47	0.01
2005	0.43	0.37	0.37	0.43	0.01
2006	0.46	0.38	0.40	0.45	0.02
2007	0.41	0.37	0.37	0.41	0.01
2008	0.38	0.35	0.37	0.43	0.01
2009	0.33	0.30	0.32	0.37	0.00
2010	0.37	0.31	0.33	0.40	0.00
2011	0.38	0.33	0.34	0.41	0.00
2012	0.50	0.42	0.43	0.49	0.00
2013	0.47	0.37	0.38	0.43	0.01
2014	0.53	0.46	0.47	0.52	0.01
2015	0.51	0.42	0.43	0.47	0.01
Average	0.36	0.29	0.29	0.35	0.01
Trend	0.00952***	0.0114***	0.0120***	0.0114***	0.000
(t-value)	[8.227]	[11.15]	[11.91]	[10.58]	[0.47]

Table A2: Alternative definitions of earnings: Cash flow predictability over time

Table A2 presents results of regressions, estimated annually, of current operating cash flows on lagged earnings, accruals, and cash flows for the period 1989-2015. CF is defined as net cash flow from operating activities less cash flow from extraordinary items and discontinued operations [Compustat: OANCF - XIDOC]. EAR1 is defined as pretax income less special items [Compustat: PI – SPI]. EAR2 is defined as operating income after depreciation [Compustat: OIADP]. EAR3 is defined as operating income before depreciation [Compustat: OIBDP]. SPI is defined as special items [Compustat: SPI].

Adj. R²_{EAR1} is the explanatory power of the following regression model estimated by year:

$$CF_{i,t} = \beta_0 + \beta^{\text{EAR1}} EAR1_{i,t-1} + \varepsilon_{i,t}$$

Adj. R²_{EAR2} is the explanatory power of the following regression model estimated by year:

 $CF_{i,t} = \beta_0 + \beta^{\text{EAR2}} EAR2_{i,t-1} + \varepsilon_{i,t}$

Adj. R²_{EAR3} is the explanatory power of the following regression model estimated by year:

$$CF_{i,t} = \beta_0 + \beta^{\text{EAR3}} EAR3_{i,t-1} + \varepsilon_{i,t}$$

Adj. R²_{CF} is the explanatory power of the following regression model estimated by year:

 $CF_{i,t} = \beta_0 + \beta^{CF} CF_{i,t-1} + \varepsilon_{i,t}$ Adj. R²_{SPI} is the explanatory power of the following regression model estimated by year:

 $CF_{i,t} = \beta_0 + \beta^{\text{SPI}} SPI_{i,t-1} + \varepsilon_{i,t}$

Trend is the coefficient estimate obtained by regressing yearly estimates (Adj. R²) obtained from each specification above on the time variable. Average is average explanatory power over the sample period. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels (two-tailed p-values), respectively.

$FCF_{i,t} =$	$\beta_0 + \beta^{EAF}$	$e^{RN}EARN_{i,t-1} + \varepsilon_{i,t}$	$\beta_0 + \beta^{\text{FCF}} FCF_{i,t-1} + \varepsilon_{i,t}$		$\beta_0 + \beta^{ACC}$	$ACC_{i,t-1} + \varepsilon_{i,t}$
Year	β^{EARN}	Adj. R ² _{EARN}	β^{FCF}	Adj. R ² _{FCF}	β^{ACC}	Adj. R ² _{ACC}
	(1)	(2)	(3)	(4)	(5)	(6)
1989	0.06	0.00	0.35	0.04	-0.25	0.01
1990	0.13	0.00	0.34	0.05	-0.12	0.00
1991	0.17	0.01	0.37	0.07	-0.06	0.00
1992	0.11	0.00	0.35	0.03	-0.09	0.00
1993	0.11	0.00	0.37	0.06	-0.16	0.01
1994	0.24	0.01	0.45	0.08	-0.08	0.00
1995	0.22	0.02	0.39	0.09	-0.09	0.00
1996	0.26	0.02	0.43	0.07	0.00	0.00
1997	0.37	0.07	0.45	0.16	0.00	0.00
1998	0.31	0.06	0.47	0.18	0.00	0.00
1999	0.37	0.12	0.48	0.20	0.07	0.00
2000	0.46	0.13	0.53	0.18	0.10	0.00
2001	0.30	0.08	0.39	0.12	0.09	0.00
2002	0.28	0.03	0.48	0.06	0.09	0.00
2003	0.36	0.08	0.36	0.09	0.08	0.00
2004	0.45	0.09	0.54	0.13	-0.03	0.00
2005	0.43	0.09	0.60	0.18	0.04	0.00
2006	0.45	0.15	0.59	0.26	0.03	0.00
2007	0.41	0.13	0.56	0.28	0.09	0.00
2008	0.40	0.09	0.53	0.22	-0.02	0.00
2009	0.23	0.08	0.46	0.22	0.06	0.00
2010	0.35	0.05	0.51	0.09	0.05	0.00
2011	0.47	0.11	0.62	0.20	0.07	0.00
2012	0.56	0.17	0.69	0.30	0.06	0.00
2013	0.50	0.18	0.66	0.33	0.11	0.00
2014	0.56	0.15	0.63	0.24	0.19	0.01
2015	0.52	0.21	0.62	0.33	0.11	0.00
Average		0.08		0.16		0.00
Trend		0.007***		0.009***		-0.000
(t-value)		[8.01]		[6.93]		[-0.54]

Table A3: Alternative definitions of cash flows: Cash flow predictability over time

Table A3 presents results of regressions, estimated annually, of current period free cash flows on lagged earnings, accruals, and free cash flows for the period 1989-2015.

EARN is defined as income before extraordinary items and discontinued operations [Compustat: IB]

CF is defined as net cash flow from operating activities less cash flow from extraordinary items and discontinued operations [Compustat: *OANCF* – *XIDOC*].

FCF is defined as cash flows from operations-increase in required cash +cash interest paid – tax shield –cash flow from investing [Compustat: OANCF - XIDOC + INTPN - ((PI-NI)/PI)*XINT - CAPX].
ACC is defined as the difference between EARN and CF [EARN – CF].

 β^{EARN} and Adj. R^{2}_{EARN} are the coefficient estimate and explanatory power, respectively, of the following regression model estimated by year:

$$FCF_{i,t} = \beta_0 + \beta^{\text{EARN}} EARN_{i,t-1} + \varepsilon_{i,t}$$

 β^{FCF} and Adj. R^{2}_{FCF} are the coefficient estimate and explanatory power, respectively, of the following regression model estimated by year:

$$FCF_{i,t} = \beta_0 + \beta^{FCF}FCF_{i,t-1} + \varepsilon_{i,t}$$

 β^{ACC} and Adj. R^{2}_{ACC} are the coefficient estimate and explanatory power, respectively, of the following regression model estimated by year:

$$FCF_{i,t} = \beta_0 + \beta^{ACC}ACC_{i,t-1} + \varepsilon_{i,t}$$

Trend is the coefficient estimate obtained by regressing yearly estimates ((β /Adj. R²)) obtained from each specification above on the time variable. *Average* is average explanatory power over the sample period. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels (two-tailed p-values), respectively.

β^{EARN}	Adj. R ² _{EARN}	β^{CF}	Adj. R ² _{CF}	β^{ACC}	Adj. R ² _{ACC}
(1)	(2)	(3)	(4)	(5)	(6)
Firms with atle	ast 12 observations				
0.27	0.13	0.30	0.14	-0.02	0.04
Firms with atle	ast 16 observations				
0.30	0.14	0.32	0.15	-0.03	0.04
Firms with atle	ast 20 observations				
0.32	0.14	0.33	0.16	-0.05	0.04
Firms with atle	ast 24 observations				
0.35	0.14	0.32	0.16	-0.05	0.04
Constant sample	e (Firms with 27 observe	ations)			
0.37	0.14	0.32	0.16	-0.06	0.04

Table A4: Alternative research design: Time-series regression analysis

Table A4 presents mean value of estimates obtained from firm-specific time-series regressions, of current period cash flows on lagged earnings, accruals, and cash flows for the period 1989-2015.

EARN is computed as income before extraordinary items and discontinued operations [Compustat: *IB*]. CF is computed as net cash flow from operating activities less cash flow from extraordinary items and discontinued operations [Compustat: OANCF - XIDOC]. ACC is the total operating accruals, estimated as income before extraordinary items and discontinued operations minus net cash flow from operating activities less cash flow from extraordinary items and discontinued operations minus net cash flow from operating activities less cash flow from extraordinary items and discontinued operations minus net cash flow from operating activities less cash flow from extraordinary items and discontinued operations [*EARN* – *CF*].

 β^{EARN} and Adj. R^2_{EARN} are the mean values of the coefficient estimate and explanatory power, respectively, of the following regression model estimated separately for each firm i in the sample:

$$CF_{i,t} = \beta_0 + \beta^{\text{EARN}} EARN_{i,t-1} + \varepsilon_{i,t}$$

 β^{CF} and Adj. R^2_{CF} are the mean values of the coefficient estimate and explanatory power, respectively, of the following regression model estimated separately for each firm i in the sample:

$$CF_{i,t} = \beta_0 + \beta^{CF} CF_{i,t-1} + \varepsilon_{i,t}$$

 β^{ACC} and Adj. R^2_{ACC} are the mean values of the coefficient estimate and explanatory power, respectively, of the following regression model estimated separately for each firm i in the sample:

$$CF_{i,t} = \beta_0 + \beta^{ACC} ACC_{i,t-1} + \varepsilon_{i,t}$$

*, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels (two-tailed p-values), respectively.

$CF_{i,t} =$	$\beta_0 + \beta^{EAF}$	$R^{N}EARN_{i,t-1} + \varepsilon_{i,t}$	$\beta_0 + \beta_0$	$CFCF_{i,t-1} + \varepsilon_{i,t}$	$\beta_0 + \beta^{ACC}$	$EACC_{i,t-1} + \varepsilon_{i,t}$
Year	β^{EARN}	Adj. R ² _{EARN}	β^{CF}	Adj. R ² _{CF}	β^{ACC}	Adj. R ² _{ACC}
	(1)	(2)	(3)	(4)	(5)	(6)
1989	0.49	0.15	0.65	0.40	-0.34	0.09
1990	0.66	0.36	0.75	0.50	-0.21	0.02
1991	0.68	0.40	0.63	0.42	-0.14	0.01
1992	0.54	0.30	0.76	0.51	-0.18	0.02
1993	0.65	0.40	0.70	0.48	-0.07	0.00
1994	0.58	0.30	0.79	0.53	-0.21	0.03
1995	0.65	0.29	0.67	0.44	-0.42	0.09
1996	0.66	0.28	0.66	0.32	-0.07	0.00
1997	0.75	0.35	0.76	0.53	-0.39	0.08
1998	0.54	0.22	0.77	0.52	-0.40	0.09
1999	0.55	0.25	0.68	0.47	-0.30	0.06
2000	0.68	0.29	0.72	0.40	-0.30	0.04
2001	0.63	0.30	0.61	0.35	-0.18	0.02
2002	0.31	0.24	0.69	0.53	0.01	0.00
2003	0.37	0.29	0.73	0.45	0.11	0.02
2004	0.58	0.32	0.78	0.56	-0.32	0.05
2005	0.75	0.41	0.86	0.68	-0.53	0.12
2006	0.81	0.50	0.82	0.62	-0.36	0.05
2007	0.80	0.47	0.87	0.63	-0.30	0.03
2008	0.58	0.33	0.80	0.59	-0.31	0.05
2009	0.30	0.23	0.61	0.49	-0.03	0.00
2010	0.49	0.25	0.77	0.58	-0.36	0.08
2011	0.77	0.45	0.84	0.68	-0.53	0.11
2012	0.74	0.45	0.83	0.67	-0.48	0.10
2013	0.62	0.40	0.82	0.73	-0.35	0.07
2014	0.81	0.48	0.91	0.69	-0.41	0.07
2015	0.78	0.41	0.81	0.55	-0.30	0.04
Average		0.34		0.53		0.05
Trend		0.005**		0.009***		0.001
(t-value)		[2.60]		[4.68]		[1.52]

Table A5: Alternative sample selection: Cash flow predictability over time

Table A5, Panel A: Cash flow predictability over time: S&P 500 firms

$CF_{i,t} =$	$\beta_0 + \beta^{EAF}$	$ext{RN}EARN_{i,t-1} + \varepsilon_{i,t}$	$\beta_0 + \beta^0$	$CFCF_{i,t-1} + \varepsilon_{i,t}$	$\beta_0 + \beta^{ACC}$	$ACC_{i,t-1} + \varepsilon_{i,t}$
Year	β^{EARN}	Adj. R ² _{EARN}	β^{CF}	Adj. R ² _{CF}	β^{ACC}	Adj. R ² _{ACC}
	(1)	(2)	(3)	(4)	(5)	(6)
1989	0.51	0.13	0.56	0.27	-0.29	0.06
1990	0.42	0.11	0.48	0.21	-0.20	0.03
1991	0.38	0.11	0.49	0.21	-0.17	0.03
1992	0.32	0.08	0.50	0.22	-0.20	0.04
1993	0.35	0.10	0.53	0.25	-0.20	0.04
1994	0.39	0.14	0.59	0.30	-0.15	0.02
1995	0.36	0.12	0.52	0.26	-0.20	0.04
1996	0.44	0.15	0.54	0.23	-0.11	0.01
1997	0.47	0.22	0.59	0.31	-0.07	0.00
1998	0.40	0.18	0.60	0.33	-0.11	0.01
1999	0.43	0.22	0.59	0.31	-0.01	0.00
2000	0.54	0.22	0.69	0.28	0.05	0.00
2001	0.37	0.21	0.57	0.30	0.07	0.00
2002	0.33	0.22	0.62	0.36	0.08	0.01
2003	0.46	0.31	0.67	0.40	0.07	0.00
2004	0.58	0.33	0.74	0.47	-0.15	0.01
2005	0.54	0.31	0.68	0.41	-0.07	0.00
2006	0.58	0.32	0.74	0.46	-0.10	0.00
2007	0.51	0.31	0.64	0.39	-0.02	0.00
2008	0.52	0.29	0.62	0.36	-0.09	0.00
2009	0.31	0.18	0.57	0.31	0.03	0.00
2010	0.43	0.24	0.62	0.35	-0.05	0.00
2011	0.51	0.26	0.69	0.36	-0.05	0.00
2012	0.62	0.35	0.78	0.49	-0.13	0.01
2013	0.52	0.29	0.77	0.45	-0.06	0.00
2014	0.61	0.41	0.77	0.52	-0.03	0.00
2015	0.53	0.36	0.73	0.50	0.00	0.00
Average		0.23		0.34		0.01
Trend		0.010***		0.010***		-0.002***
(t-value)		[8.50]		[8.10]		[-5.74]

Table A5, Panel B: Cash flow predictability over time: NON S&P 500 firms

$CF_{i,t} =$	$\beta_0 + \beta^{EAF}$	$ext{RN}EARN_{i,t-1} + \varepsilon_{i,t}$	$\beta_0 + \beta^0$	$CFCF_{i,t-1} + \varepsilon_{i,t}$	$\beta_0 + \beta^{ACC}$	$ACC_{i,t-1} + \varepsilon_{i,t}$
Year	β^{EARN}	Adj. R ² _{EARN}	β^{CF}	Adj. R ² _{CF}	β^{ACC}	Adj. R ² _{ACC}
	(1)	(2)	(3)	(4)	(5)	(6)
1990	0.33	0.07	0.40	0.13	-0.13	0.01
1991	0.32	0.07	0.42	0.13	-0.12	0.01
1992	0.29	0.07	0.43	0.16	-0.15	0.02
1993	0.34	0.09	0.49	0.20	-0.14	0.02
1994	0.39	0.14	0.54	0.23	-0.05	0.00
1995	0.30	0.09	0.44	0.16	-0.09	0.01
1996	0.46	0.17	0.51	0.19	-0.02	0.00
1997	0.50	0.24	0.55	0.22	0.10	0.01
1998	0.39	0.18	0.55	0.25	0.03	0.00
1999	0.44	0.22	0.58	0.25	0.16	0.01
2000	0.63	0.21	0.75	0.21	0.31	0.02
2001	0.38	0.20	0.59	0.27	0.12	0.01
2002	0.33	0.21	0.60	0.32	0.10	0.01
2003	0.50	0.35	0.65	0.36	0.16	0.02
2004	0.59	0.33	0.74	0.43	-0.02	0.00
2005	0.54	0.30	0.65	0.34	0.02	0.00
2006	0.58	0.32	0.79	0.43	0.03	0.00
2007	0.53	0.34	0.65	0.36	0.18	0.02
2008	0.56	0.35	0.62	0.34	0.12	0.01
2009	0.34	0.20	0.65	0.34	0.07	0.00
2010	0.43	0.25	0.60	0.33	0.01	0.00
2011	0.56	0.28	0.71	0.31	0.11	0.00
2012	0.71	0.38	0.86	0.48	-0.03	0.00
2013	0.57	0.30	0.80	0.41	0.04	0.00
2014	0.66	0.45	0.79	0.48	0.11	0.00
2015	0.57	0.38	0.75	0.50	0.06	0.00
Average		0.24		0.30		0.01
Trend		0.013***		0.013***		-0.000**
(t-value)		[8.62]		[10.51]		[-2.55]

Table A5, Panel C: Cash flow predictability over time: Largest 1000 firms

$CF_{i,t} =$	$\beta_0 + \beta^{EAB}$	$RNEARN_{i,t-1} + \varepsilon_{i,t}$	$\beta_0 + \beta^0$	$CFCF_{i,t-1} + \varepsilon_{i,t}$	$\beta_0 + \beta^{ACC}$	$ACC_{i,t-1} + \varepsilon_{i,t}$
Year	β^{EARN}	Adj. R ² _{EARN}	β^{CF}	Adj. R ² _{CF}	β^{ACC}	Adj. R ² _{ACC}
	(1)	(2)	(3)	(4)	(5)	(6)
1990	0.57	0.23	0.61	0.39	-0.29	0.06
1991	0.50	0.21	0.59	0.35	-0.22	0.04
1992	0.42	0.15	0.62	0.35	-0.25	0.05
1993	0.41	0.14	0.60	0.34	-0.26	0.06
1994	0.41	0.14	0.64	0.37	-0.22	0.05
1995	0.44	0.15	0.58	0.36	-0.30	0.08
1996	0.44	0.14	0.58	0.27	-0.18	0.02
1997	0.44	0.18	0.60	0.36	-0.20	0.04
1998	0.38	0.15	0.62	0.38	-0.22	0.04
1999	0.41	0.20	0.59	0.35	-0.15	0.02
2000	0.47	0.25	0.63	0.38	-0.14	0.01
2001	0.37	0.21	0.55	0.32	-0.01	0.00
2002	0.32	0.21	0.65	0.39	0.04	0.00
2003	0.39	0.25	0.67	0.43	-0.01	0.00
2004	0.59	0.31	0.75	0.50	-0.29	0.05
2005	0.55	0.31	0.70	0.48	-0.19	0.02
2006	0.56	0.30	0.68	0.45	-0.20	0.02
2007	0.50	0.25	0.62	0.40	-0.19	0.02
2008	0.47	0.20	0.63	0.39	-0.27	0.05
2009	0.26	0.15	0.50	0.29	-0.02	0.00
2010	0.43	0.21	0.68	0.39	-0.13	0.01
2011	0.48	0.24	0.70	0.47	-0.30	0.06
2012	0.48	0.28	0.67	0.53	-0.25	0.05
2013	0.44	0.24	0.73	0.54	-0.23	0.04
2014	0.50	0.27	0.73	0.55	-0.25	0.05
2015	0.42	0.24	0.65	0.45	-0.14	0.02
Average		0.22		0.40		0.03
Trend		0.004***		0.006***		-0.001
(t-value)		[3.31]		[4.22]		[-1.32]

Table A5, Panel D: Cash flow predictability over time: Non-largest 1000 firms

$CF_{i,t} =$	$\beta_0 + \beta^{EAF}$	$RNEARN_{i,t-1} + \varepsilon_{i,t}$	$\beta_0 + \beta^0$	$CFCF_{i,t-1} + \varepsilon_{i,t}$	$\beta_0 + \beta^{ACC} A$	$ACC_{i,t-1} + \varepsilon_{i,t}$
Year	β^{Earn}	Adj. R ² _{EARN}	β^{CF}	Adj. R ² _{CF}	β^{ACC}	Adj. R ² _{ACC}
	(1)	(2)	(3)	(4)	(5)	(6)
1990	0.55	0.25	0.53	0.34	-0.23	0.04
1991	0.61	0.26	0.63	0.38	-0.24	0.04
1992	0.60	0.30	0.63	0.41	-0.20	0.03
1993	0.59	0.22	0.74	0.43	-0.40	0.08
1994	0.52	0.18	0.62	0.31	-0.22	0.03
1995	0.62	0.22	0.61	0.38	-0.39	0.11
1996	0.55	0.22	0.61	0.33	-0.22	0.03
1997	0.57	0.24	0.57	0.35	-0.24	0.05
1998	0.63	0.28	0.67	0.44	-0.27	0.06
1999	0.55	0.21	0.59	0.35	-0.30	0.07
2000	0.76	0.30	0.69	0.40	-0.36	0.06
2001	0.51	0.17	0.51	0.26	-0.31	0.06
2002	0.52	0.25	0.54	0.35	-0.19	0.04
2003	0.40	0.23	0.59	0.37	-0.08	0.00
2004	0.66	0.27	0.71	0.44	-0.42	0.09
2005	0.73	0.34	0.59	0.35	-0.23	0.03
2006	0.60	0.26	0.60	0.36	-0.27	0.04
2007	0.66	0.32	0.57	0.31	-0.11	0.01
2008	0.51	0.24	0.63	0.38	-0.19	0.02
2009	0.21	0.10	0.47	0.25	-0.03	0.00
2010	0.34	0.13	0.49	0.26	-0.15	0.02
2011	0.56	0.28	0.72	0.47	-0.23	0.03
2012	0.57	0.34	0.68	0.52	-0.21	0.03
2013	0.53	0.30	0.78	0.52	-0.15	0.02
2014	0.55	0.28	0.69	0.49	-0.29	0.06
2015	0.57	0.33	0.69	0.49	-0.18	0.02
Average		0.25		0.38		0.04
Trend		0.002		0.003*		-0.001**
(t-value)		[1.05]		[1.76]		[-2.10]

Table A5, Panel E: Cash flow predictability over time: Constant sample (1990-2015) firms

Table A5 presents results of regressions, estimated annually, of current operating cash flows on lagged earnings, accruals, and cash flows. EARN is computed as income before extraordinary items and discontinued operations [Compustat: *IB*]. CF is computed as net cash flow from operating activities less cash flow from extraordinary items and discontinued operations [Compustat: OANCF - XIDOC]. ACC is the total operating accruals, estimated as income before extraordinary items and discontinued operations minus net cash flow from operating activities less cash flow from extraordinary items and discontinued operations minus net cash flow from operating activities less cash flow from extraordinary items and discontinued operations minus net cash flow from operating activities less cash flow from extraordinary items and discontinued operations [*EARN* – *CF*]

Panel A presents the results for firms included in the S&P 500 index spanning the period 1989-2015. Panel B presents the results for firms excluded from the S&P 500 index spanning the period 1989-2015. Panel C presents the results

for the largest 1000 firms based on total assets spanning the period 1990-2015. Panel D presents the results for all firms excluding the largest 1000 firms based on total assets spanning the period 1990-2015. Panel E presents the results based on a constant sample of 748 firms spanning the period 1990-2015.

 β^{EARN} and Adj. R^2_{EARN} are the coefficient estimate and explanatory power, respectively, of the following regression model estimated by year:

$$CF_{i,t} = \beta_0 + \beta^{\text{EARN}} EARN_{i,t-1} + \varepsilon_{i,t}$$

 β^{CF} and Adj. R^{2}_{CF} are the coefficient estimate and explanatory power, respectively, of the following regression model estimated by year:

$$CF_{i,t} = \beta_0 + \beta^{CF} CF_{i,t-1} + \varepsilon_{i,t}$$

 β^{ACC} and Adj. R^{2}_{ACC} are the coefficient estimate and explanatory power, respectively, of the following regression model estimated by year:

$$CF_{i,t} = \beta_0 + \beta^{ACC} ACC_{i,t-1} + \varepsilon_{i,t}$$

Trend is the coefficient estimate obtained by regressing yearly estimates ((β /Adj. R²)) obtained from each specification above on the time variable. *Average* is average explanatory power over the sample period. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels (two-tailed p-values), respectively.

Year	β^{CHG_AR}	β^{CHG_INV}	β^{CHG_AP}	β^{DEPR}	β^{AMORT}	β^{OTHER}	β^{CF}
1989	0.46	0.28	-0.55	0.43	0.18	0.23	0.63
1990	0.45	0.32	-0.65	0.41	0.33	0.22	0.61
1991	0.41	0.26	-0.61	0.25	-0.14	0.09	0.60
1992	0.33	0.28	-0.52	0.46	0.35	0.08	0.59
1993	0.37	0.24	-0.49	0.40	0.16	0.10	0.61
1994	0.33	0.16	-0.61	0.33	0.21	0.17	0.66
1995	0.30	0.08	-0.39	0.25	-1.12	0.08	0.59
1996	0.25	0.31	-0.55	0.14	-0.95	0.19	0.66
1997	0.30	0.39	-0.51	0.15	-0.15	0.15	0.70
1998	0.30	0.12	-0.40	0.06	-0.42	0.09	0.67
1999	0.34	0.31	-0.46	0.09	-0.56	0.13	0.67
2000	0.51	0.34	-0.70	0.24	-1.05	0.21	0.76
2001	0.41	0.20	-0.52	0.31	-0.34	0.10	0.60
2002	0.54	0.30	-0.53	0.11	0.08	0.08	0.67
2003	0.64	0.44	-0.57	0.26	-0.05	0.08	0.73
2004	0.38	0.43	-0.55	0.18	-0.32	0.09	0.79
2005	0.51	0.38	-0.58	0.11	-0.03	0.14	0.76
2006	0.50	0.35	-0.56	0.15	-0.34	0.19	0.80
2007	0.55	0.48	-0.56	0.16	-0.07	0.17	0.72
2008	0.65	0.29	-0.53	0.34	0.05	0.15	0.69
2009	0.48	0.49	-0.59	0.16	0.39	0.09	0.62
2010	0.42	0.44	-0.56	0.31	0.18	0.13	0.68
2011	0.50	0.22	-0.49	0.24	0.15	0.20	0.75
2012	0.58	0.65	-0.75	0.13	0.08	0.20	0.85
2013	0.58	0.49	-0.79	0.07	0.03	0.14	0.83
2014	0.57	0.37	-0.69	0.06	0.00	0.21	0.82
2015	0.41	0.39	-0.46	0.00	0.09	0.13	0.77
Average	0.45	0.33	-0.56	0.21	-0.12	0.14	0.77
Trend	0.008***	0.009***	-0.003	-0.010***	0.009	0.001	0.008***
(t-value)	[3.58]	[3.65]	[-1.50]	[-3.85]	[0.86]	[0.51]	[5.39]

Panel A: Disaggregating accruals into six major components

Year	β^{ACC_EST}	β^{ACC_DELTA}	β^{CF}
	(1)	(2)	(3)
1989	0.09	0.38	0.65
1990	0.03	0.46	0.63
1991	0.03	0.43	0.64
1992	0.00	0.35	0.64
1993	0.06	0.34	0.65
1994	0.06	0.39	0.72
1995	0.01	0.33	0.62
1996	0.16	0.39	0.69
1997	0.14	0.41	0.73
1998	0.04	0.34	0.69
1999	0.10	0.37	0.68
2000	0.16	0.58	0.79
2001	0.05	0.55	0.64
2002	0.04	0.50	0.70
2003	0.08	0.54	0.75
2004	0.04	0.49	0.82
2005	0.14	0.50	0.78
2006	0.14	0.53	0.84
2007	0.15	0.54	0.74
2008	0.04	0.56	0.73
2009	0.06	0.46	0.65
2010	0.05	0.54	0.74
2011	0.07	0.46	0.79
2012	0.16	0.48	0.87
2013	0.11	0.50	0.85
2014	0.12	0.47	0.84
2015	0.09	0.41	0.77
Average	0.08	0.46	0.73
Trend	0.002*	0.005***	0.007***
(t-value)	[2.00]	[3.15]	[5.64]

Panel B: Disaggregating accruals based on magnitude of managerial estimates

Table A6 reports results of regressions, estimated annually, of current operating cash flows on lagged accrual components and lagged cash flows for the period 1989-2015.

Panel A reports the estimation results after decomposing accruals into its major components based on Barth et al. (2001). β^{CHG_AR} , β^{CHG_INV} , β^{CHG_AP} , β^{DEPR} , β^{AMORT} , β^{OTHER} , and β^{CF} are the coefficient estimates on change in accounts receivable, change in inventory, change in accounts payable, depreciation, amortization, other accruals and cash flows, respectively, of the following regression model estimated by year:

 $CF_{i,t} = \beta_0 + \beta^{CHG_AR} CHG_AR_{i,t-1} + \beta^{CHG_INV} CHG_INV_{i,t-1} + \beta^{CHG_AP} CHG_AP_{i,t-1} + \beta^{DEPR} DEPR_{i,t-1} + \beta^{AMORT} AMORT_{i,t-1} + \beta^{OTHER} OTHER_{i,t-1} + \beta^{CF} CF_{i,t-1} + \varepsilon_{i,t}$

Panel B reports the estimation results after decomposing accruals into components based on Lev et al. (2010).

 β^{ACC_EST} , β^{ACC_DELTA} , and β^{CF} are the coefficient estimates on accrual component with significant managerial estimates, accrual components unaffected by managerial estimates, and cash flows, respectively, of the following regression model estimated by year: $CF_{i,t} = \beta_0 + \beta^{ACC_EST} ACC_EST_{i,t-1} + \beta^{ACC_DELTA} ACC_DELTA_{i,t-1} + \beta^{CF} CF_{i,t-1} + \varepsilon_{i,t}$

Trend is the coefficient estimate obtained by regressing yearly estimates (β) obtained from the specification above on the time variable. All other variables are described in Table 2. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels (two-tailed p-values), respectively.

$CF_{i,t} =$	$\beta_0 + \beta^{\text{EARN}} EA$	$RN_{i,t-1} + \varepsilon_{i,t}$	$\beta_0 + \beta^{CF}$	$CF_{i,t-1} + \varepsilon_{i,t}$
	Adj. R ²	EARN	Adj.	R^2 CF
	S 1	S2	S 1	S2
1990	0.20	0.17	0.11	0.04
1991	0.23	0.32	0.10	0.14
1992	0.27	0.14	0.16	0.09
1993	0.19	0.28	0.14	0.16
1994	0.13	0.30	0.17	0.18
1995	0.16	0.25	0.10	0.16
1996	0.30	0.31	0.24	0.24
1997	0.31	0.31	0.24	0.22
1998	0.25	0.39	0.19	0.28
1999	0.25	0.24	0.21	0.23
2000	0.30	0.23	0.30	0.18
2001	0.17	0.34	0.20	0.24
2002	0.25	0.29	0.19	0.22
2003	0.20	0.22	0.17	0.15
2004	0.23	0.29	0.19	0.23
2005	0.16	0.41	0.13	0.32
2006	0.30	0.37	0.24	0.24
2007	0.31	0.25	0.25	0.20
2008	0.24	0.17	0.18	0.13
2009	0.25	0.13	0.25	0.10
2010	0.20	0.41	0.16	0.29
2011	0.30	0.42	0.28	0.31
2012	0.45	0.48	0.44	0.42
2013	0.27	0.27	0.24	0.21
2014	0.25	0.30	0.28	0.27
2015	0.29	0.28	0.22	0.22
Average	0.25	0.29	0.21	0.21
Trend	0.00**	0.00	0.01***	0.01***
t-value	[2.08]	[1.46]	[3.46]	[3.04]

Table A7: Cash flow predictability over time: Semi-annual frequency

Table A7 reports explanatory power of regressions estimated semi-annually, of current operating cash flows on lagged earnings and cash flows for the period 1989-2015. EARN is computed as income before extraordinary items and discontinued operations [Compustat: IB]. CF is computed as net cash flow from operating activities less cash flow from extraordinary items and discontinued operations [Compustat: OANCF - XIDOC]. ACC is the total operating accruals, estimated as income before extraordinary items and discontinued operations minus net cash flow from operating activities less cash flow from extraordinary items and discontinued operations [EARN - CF].

Adj. R^{2}_{EARN} is the explanatory power of the following regression model estimated semi-annually: $CF_{i,t} = \beta_0 + \beta^{EARN} EARN_{i,t-1} + \varepsilon_{i,t}$

Adj. R²_{CF} is the explanatory power of the following regression model estimated semi-annually:

$$CF_{i,t} = \beta_0 + \beta^{CF} CF_{i,t-1} + \varepsilon_{i,t}$$

Trend is the coefficient estimate obtained by regressing semi-annual explanatory power (Adj. R^2) obtained from each specification above on the time variable. *Average* is average explanatory power. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels (two-tailed p-values), respectively.

Year	$\beta^{(CF-ACC)}$	Adj. R ² (CF- ACC)	Adj. R ² EARN	Adj. R ² _{CF}	Adj. R ² CF,ACC	Inc. R ² : ACC	Inc. R ² : CF
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1998	-0.45	0.27	0.20	0.35	0.36	0.01	0.29
1999	-0.36	0.18	0.27	0.40	0.43	0.02	0.40
2000	-0.35	0.13	0.22	0.34	0.35	0.01	0.32
2001	-0.13	0.02	0.30	0.37	0.39	0.02	0.39
2002	-0.14	0.03	0.32	0.40	0.42	0.02	0.42
2003	-0.19	0.06	0.32	0.41	0.43	0.02	0.42
2004	-0.24	0.11	0.36	0.49	0.50	0.01	0.50
2005	-0.25	0.10	0.32	0.40	0.42	0.02	0.41
2006	-0.15	0.05	0.43	0.49	0.51	0.03	0.51
2007	-0.14	0.04	0.48	0.51	0.54	0.03	0.54
2008	-0.06	0.00	0.50	0.54	0.58	0.05	0.58
2009	-0.03	0.00	0.40	0.48	0.52	0.04	0.50
2010	-0.06	0.01	0.39	0.45	0.47	0.02	0.46
2011	-0.07	0.01	0.45	0.53	0.54	0.02	0.54
2012	0.00	0.00	0.50	0.52	0.56	0.04	0.55
2013	-0.04	0.00	0.59	0.62	0.66	0.04	0.64
2014	0.00	0.00	0.52	0.57	0.59	0.02	0.58
2015	-0.04	0.00	0.50	0.60	0.62	0.02	0.61
Average	-0.15	0.06	0.39	0.47	0.49	0.02	0.48
Trend (t-value)	0.0216*** [7.17]	-0.0109*** [-4.92]	0.0189* [8.63]	0.0143*** [8.27]	0.0152** [7.99]	0.0009* [1.91]	0.0166*** [8.06]

 Table A8: Accrual-Cash flow relation and Cash flow predictability over time: European Union (EU) sample firms

Table A8 presents the correlation between accruals and cash flows, and the operating cash flow predictability of earnings and cash flows for the period 1998-2015 using a sample of international firms from eight EU jurisdictions that adopted IFRS starting 2005. The sample comprises of 36,065 observations based on annual data corresponding to the following jurisdictions: Germany, Denmark, France, UK, Italy, The Netherlands, Norway, and Sweden.

 β (^{CF-ACC)} and Adj. R²_{CF-ACC} are the coefficient estimate and explanatory power, respectively, of the following regression model estimated by year:

$$ACC_{i,t} = \beta_0 + \beta^{(\text{ACC-CF})} CF_{i,t} + \varepsilon_{i,t}$$

Adj. R^2_{EARN} is the explanatory power of the following regression model estimated by year:

$$CF_{i,t} = \beta_0 + \beta^{\text{EARN}} EARN_{i,t-1} + \varepsilon_{i,t}$$

Adj. R²_{CF} is the explanatory power of the following regression model estimated by year:

 $CF_{i,t} = \beta_0 + \beta^{CF} CF_{i,t-1} + \varepsilon_{i,t}$ Adj. R²_{CF,ACC} is the explanatory power of the following regression model estimated by year:

$$CF_{i,t} = \beta_0 + \beta_1^{ACC} ACC_{i,t-1} + \beta_1^{CF} CF_{i,t-1} + \varepsilon_{i,t},$$

Inc. R²: ACC and Inc. R²: CF refer to the incremental explanatory power of accruals and cash flows respectively. *Trend* is the coefficient estimate obtained by regressing yearly estimates ((β /Adj. R²)) obtained from each specification above on the time variable. All other variables are described in Table 2. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels (two-tailed p-values), respectively.

DM/CW Statistic (*100)	Ben	chmark Model: Lagge	ed Cash Flow Mo	del
Performance of Alt. Model:	(1)	(2)	(3)	(4)
1990	-0.13	-0.22	0.05	0.16
1991	-0.10	-0.21	0.04	0.14
1992	-0.14	-0.21	0.03	0.12
1993	-0.16	-0.24	0.02	0.12
1994	-0.20	-0.36	0.04	0.13
1995	-0.19	-0.29	0.04	0.11
1996	-0.14	-0.37	0.05	0.09
1997	-0.15	-0.52	0.12	0.15
1998	-0.27	-0.53	0.07	0.09
1999	-0.17	-0.56	0.06	0.09
2000	-0.16	-0.72	0.09	0.17
2001	-0.20	-0.48	0.10	0.18
2002	-0.22	-0.48	0.07	0.13
2003	-0.15	-0.50	0.05	0.13
2004	-0.23	-0.68	0.04	0.11
2005	-0.15	-0.60	0.06	0.10
2006	-0.19	-0.70	0.08	0.12
2007	-0.11	-0.56	0.08	0.15
2008	-0.11	-0.46	0.07	0.14
2009	-0.32	-0.37	0.06	0.12
2010	-0.15	-0.39	0.03	0.13
2011	-0.18	-0.53	0.06	0.10
2012	-0.21	-0.70	0.06	0.11
2013	-0.27	-0.73	0.05	0.13
2014	-0.17	-0.74	0.05	0.10
2015	-0.20	-0.65	0.05	0.08
Average	-0.18	-0.49	0.06	0.12
Trend	-0.0024*	-0.0163***	0.0000	-0.0001
(t-value)	[-1.77]	[-5.21]	[0.68]	[-1.24]

 Table A9: Out-of-sample tests

Table A9 presents out-of-sample cash flow prediction results comparing annual estimations of alternative models (1)-(4) with the benchmark model.

$CF_{i,t} = \beta_0 + \beta^{CF} CF_{i,t-1} + \varepsilon_{i,t}$	Benchmark
$CF_{i,t} = \beta_0 + \beta^{\text{EARN}} EARN_{i,t-1} + \varepsilon_{i,t}$	Alt. Model (1)
$CF_{i,t} = \beta_0 + \beta^{ACC} ACC_{i,t-1} + \varepsilon_{i,t}$	Alt. Model (2)
$CF_{i,t} = \beta_0 + \beta^{\text{ACC}} ACC_{i,t-1} + \beta^{CF} CF_{i,t-1} + \varepsilon_{i,t}$	Alt. Model (3)
$CF_{i,t} = \beta_0 + \beta^{\text{CHG}_\text{AR}} CHG_\text{AR}_{i,t-1} + \beta^{\text{CHG}_\text{INV}} CHG_\text{INV}_{i,t-1} + \beta^{\text{CHG}_\text{AP}} CHG_\text{AP}_{i,t-1}$	
+ $\beta^{\text{DEPR}} DEPR_{i,t-1} + \beta^{\text{AMORT}} AMORT_{i,t-1} + \beta^{\text{OTHER}} OTHER_{i,t-1} + \beta^{\text{CF}} CF_{i,t-1} + \varepsilon_{i,t}$	Alt. Model (4)

Columns (1) & (2) report the Diebold-Mariano (DM, see Diebold and Mariano (1995)) statistic estimated as the difference between Mean Squared Prediction errors (MSPEs) of the benchmark model and the alternative model, for

models (1) & (2) respectively. Columns (3) & (4) report the Clark-West (CW, see Clark and West (2007)) statistic estimated as the difference between MSPEs of the benchmark model and the alternative model, for models (3) & (4) respectively. A positive test statistic implies that the cash flow predictive ability of the alternative model is superior to that of the benchmark prediction model. All positive and negative test statistics reported in Columns (1)-(4) for each sample year are statistically significant at the 1% level. *Trend* is the coefficient estimate obtained by regressing yearly DM/CW statistic on the time variable. *Average* is average DM/CW statistic over the sample period. All other variables are described in Table 2 of the paper. *, **, and *** on the *Trend* variable indicate significance at the 0.10, 0.05, and 0.01 levels (two-tailed p-values), respectively.

Year	Adj. R ² _{EARN}	Adj. R ² _{CF}	Adj. R ² CF,ACC	Inc. R ² : ACC	Inc. R ² : CF
	(1)	(2)	(3)	(4)	(5)
1990	0.14	0.14	0.18	0.03	0.16
1991	0.12	0.19	0.21	0.02	0.18
1992	0.09	0.22	0.22	0.00	0.18
1993	0.06	0.19	0.19	0.00	0.15
1994	0.11	0.22	0.23	0.01	0.20
1995	0.10	0.22	0.23	0.01	0.21
1996	0.12	0.20	0.22	0.02	0.20
1997	0.12	0.23	0.24	0.02	0.23
1998	0.11	0.22	0.23	0.01	0.21
1999	0.12	0.22	0.23	0.01	0.22
2000	0.12	0.20	0.21	0.01	0.20
2001	0.14	0.21	0.23	0.01	0.22
2002	0.10	0.16	0.17	0.00	0.17
2003	0.15	0.27	0.28	0.01	0.28
2004	0.17	0.29	0.30	0.00	0.29
2005	0.22	0.33	0.33	0.01	0.32
2006	0.20	0.33	0.34	0.01	0.32
2007	0.22	0.32	0.33	0.01	0.32
2008	0.19	0.28	0.29	0.01	0.28
2009	0.19	0.25	0.27	0.02	0.26
2010	0.12	0.28	0.28	0.00	0.28
2011	0.19	0.27	0.29	0.02	0.29
2012	0.22	0.32	0.33	0.01	0.32
2013	0.26	0.36	0.38	0.01	0.37
2014	0.27	0.43	0.44	0.01	0.43
2015	0.31	0.39	0.41	0.02	0.41
Average	0.16	0.26	0.27	0.01	0.26
Trend	0.007***	0.008***	0.008***	-0.000	0.009***
(t-value)	[7.38]	[7.59]	[7.47]	[-0.48]	[9.42]

 Table A10: Cash flow predictability over alternative horizons

Panel A: Cash flow predictability using two-year lagged Earnings, Cash Flows, and Accruals

Year	Adj. R ² _{EARN}	Adj. R ² _{CF}	Adj. R ² _{CF,ACC}	Inc. R ² : ACC	Inc. R ² : CF
	(1)	(2)	(3)	(4)	(5)
1991	0.13	0.16	0.18	0.02	0.15
1992	0.07	0.15	0.15	0.01	0.12
1993	0.06	0.14	0.15	0.00	0.12
1994	0.08	0.16	0.17	0.01	0.15
1995	0.08	0.18	0.19	0.01	0.16
1996	0.08	0.17	0.18	0.01	0.17
1997	0.09	0.20	0.21	0.01	0.17
1998	0.07	0.14	0.15	0.01	0.13
1999	0.08	0.16	0.17	0.01	0.15
2000	0.09	0.18	0.19	0.01	0.17
2001	0.08	0.15	0.16	0.00	0.15
2002	0.10	0.16	0.16	0.01	0.16
2003	0.08	0.16	0.16	0.00	0.15
2004	0.08	0.19	0.19	0.00	0.19
2005	0.12	0.21	0.22	0.00	0.22
2006	0.14	0.24	0.24	0.00	0.22
2007	0.13	0.23	0.23	0.00	0.21
2008	0.16	0.23	0.24	0.01	0.23
2009	0.13	0.16	0.18	0.01	0.17
2010	0.12	0.21	0.21	0.00	0.19
2011	0.12	0.27	0.28	0.01	0.28
2012	0.20	0.30	0.31	0.02	0.31
2013	0.16	0.23	0.24	0.00	0.23
2014	0.21	0.32	0.33	0.01	0.32
2015	0.23	0.35	0.36	0.01	0.36
Average	0.11	0.20	0.21	0.01	0.20
Trend	0.005***	0.006***	0.006***	-0.000	0.007***
(t-value)	[6.28]	[6.46]	[6.12]	[-0.06]	[7.66]

Panel B: Cash flow predictability using three-year lagged earnings, accruals, and cash flows

Table A10 reports annual estimation results for cash-flow predictability of earnings and cash flows over two-year and three-year horizons for the sample periods 1990-2015 and 1991-2015, respectively. Panel A (B) presents OLS estimation results of regressing current cash flows on two-year (three-year) lagged earnings and cash flows.

Adj. R^{2}_{EARN} is the explanatory power of the following regression model estimated by year:

$$CF_{i,t}$$
 (or $CF_{i,t+1}$) = $\beta_0 + \beta^{EARN} EARN_{i,t-1} + \varepsilon_{i,t}$,

Adj. R^{2}_{CF} is the explanatory power of the following regression model estimated by year:

$$CF_{i,t}$$
 (or $CF_{i,t+1}$) = $\beta_0 + \beta^{CF}CF_{i,t-1} + \varepsilon_{i,t}$,

Adj. R² is the explanatory power of the following regression model estimated by year: $CF_{i,t}(or CF_{i,t+1}) = \beta_0 + \beta_1^{ACC}ACC_{i,t-1} + \beta_1^{CF}CF_{i,t-1} + \varepsilon_{i,b}$

Inc. R²: ACC and Inc. R²: CF refer to the incremental explanatory power of accruals and cash flows respectively. Time Trend is the coefficient estimate obtained by regressing yearly estimates (Adj. R^2) obtained from each specification above on the time variable. *Average* is average explanatory power over the sample period. All other variables are described in Table 2 of the paper. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels (two-tailed p-values), respectively.

	Pre 1990		Wave 1	Wave 1990		Wave 2000	
	Adj. R ² _{EARN}	Adj. R ² _{CF}	Adj. R ² _{EARN}	Adj. R ² _{CF}	Adj. R ² _{EARN}	Adj. R ² _{CF}	
Year	(1)	(2)	(3)	(4)	(5)	(6)	
1989	0.14	0.28					
1990	0.14	0.24					
1991	0.14	0.23					
1992	0.13	0.26	0.07	0.24			
1993	0.15	0.28	0.08	0.27			
1994	0.17	0.28	0.13	0.32			
1995	0.16	0.30	0.11	0.26			
1996	0.20	0.28	0.14	0.21			
1997	0.27	0.31	0.21	0.32			
1998	0.21	0.36	0.17	0.33			
1999	0.22	0.31	0.22	0.32			
2000	0.25	0.31	0.22	0.27			
2001	0.15	0.22	0.22	0.32			
2002	0.18	0.27	0.22	0.38	0.25	0.44	
2003	0.19	0.28	0.30	0.43	0.44	0.47	
2004	0.22	0.37	0.37	0.53	0.36	0.48	
2005	0.21	0.30	0.33	0.46	0.37	0.46	
2006	0.20	0.30	0.37	0.49	0.37	0.52	
2007	0.27	0.24	0.30	0.38	0.36	0.51	
2008	0.19	0.34	0.27	0.37	0.35	0.40	
2009	0.11	0.22	0.15	0.29	0.25	0.39	
2010	0.14	0.25	0.27	0.39	0.26	0.39	
2011	0.25	0.36	0.27	0.35	0.29	0.42	
2012	0.33	0.43	0.32	0.47	0.38	0.54	
2013	0.32	0.48	0.32	0.44	0.29	0.47	
2014	0.32	0.51	0.34	0.44	0.46	0.57	
2015	0.30	0.51	0.37	0.46	0.36	0.53	
Average	0.21	0.32	0.24	0.36	0.34	0.47	
Trend	0.005***	0.006***	0.011***	0.008***	0.001	0.004	
(t-stat)	[4.20]	[3.96]	[6.35]	[4.57]	[0.13]	[1.05]	

Table A11: Cash flow predictability over time: Cohort analysis

Table A11 presents results of regressions, estimated annually, of current operating cash flows on lagged earnings, and cash flows for each listing cohort corresponding to the sample period 1989-2015. All of the firms are divided into three listing cohorts in the following steps. The first year in which a firm's data are available in Compustat is referred to as the "listing year." All of the firms with a listing year before 1990 are classified as "pre 1990". Firms listed during the period 1990-1999 and 2000-2015 are classified as "wave 1990" and "wave 2000", respectively. Adj. R^2_{EARN} is the explanatory power of the following regression model estimated by year:

$$CF_{i,t} = \beta_0 + \beta^{\text{EARN}} EARN_{i,t-1} + \varepsilon_{i,t}$$

Adj. R²_{CF} is the explanatory power of the following regression model estimated by year:

$$CF_{i,t} = \beta_0 + \beta^{CF} CF_{i,t-1} + \varepsilon_{i,t}$$

Trend is the coefficient estimate obtained by regressing yearly estimates (Adj. R^2) obtained from each specification above on the time variable. *Average* is average explanatory power over the sample period. All other variables are described in Table 2 of the paper. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels (two-tailed p-values), respectively.

$CF_{i,t} =$	$CF_{i,t} = \beta_0 + \beta^{\text{EARN}} EARN_{i,t-1} + \varepsilon_{i,t}$		$\beta_0 + \beta_0$	$CFCF_{i,t-1} + \varepsilon_{i,t}$	$\beta_0 + \beta^{ACC} ACC_{i,t-1} + \varepsilon_{i,t}$	
Year	β^{EARN}	Adj. R ² _{EARN}	β^{CF}	Adj. R ² _{CF}	β^{ACC}	Adj. R ² _{ACC}
	(1)	(2)	(3)	(4)	(5)	(6)
1989	0.38	0.07	0.24	0.04	0.02	0.00
1990	0.54	0.15	0.28	0.07	0.11	0.01
1991	0.56	0.19	0.32	0.09	0.17	0.01
1992	0.51	0.19	0.39	0.13	0.08	0.00
1993	0.61	0.19	0.42	0.11	0.19	0.01
1994	0.53	0.19	0.41	0.12	0.12	0.01
1995	0.48	0.15	0.41	0.13	-0.03	0.00
1996	0.59	0.19	0.40	0.11	0.15	0.01
1997	0.63	0.26	0.46	0.17	0.14	0.01
1998	0.50	0.17	0.41	0.13	0.04	0.00
1999	0.54	0.21	0.41	0.13	0.16	0.01
2000	0.66	0.02	0.46	0.01	0.30	0.00
2001	0.62	0.20	0.43	0.10	0.47	0.04
2002	0.68	0.32	0.59	0.24	0.44	0.03
2003	0.56	0.31	0.44	0.23	-0.01	0.00
2004	0.71	0.32	0.57	0.25	0.05	0.00
2005	0.69	0.34	0.56	0.27	0.00	0.00
2006	0.70	0.32	0.59	0.27	0.10	0.00
2007	0.75	0.38	0.59	0.28	0.19	0.01
2008	0.76	0.27	0.55	0.17	0.24	0.01
2009	0.45	0.24	0.39	0.18	0.29	0.02
2010	0.53	0.22	0.38	0.14	0.17	0.01
2011	0.69	0.32	0.57	0.26	0.04	0.00
2012	0.75	0.34	0.62	0.26	0.24	0.01
2013	0.70	0.33	0.62	0.27	0.30	0.01
2014	0.78	0.43	0.65	0.35	0.19	0.01
2015	0.75	0.32	0.65	0.25	0.24	0.01
Average		0.25		0.18		0.01
Trend		0.009***		0.008***		0.000
(t-value)		[5.44]		[6.24]		[0.10]

Table A12: Cash flow predictability over time: After excluding non-articulating events

Panel A: Balance-sheet based approach

$CF_{i,t} =$	$\beta_0 + \beta^{\text{EARN}} EARN_{i,t-1} + \varepsilon_{i,t}$		$\beta_0 + \beta^0$	$CFCF_{i,t-1} + \varepsilon_{i,t}$	$\beta_0 + \beta^{ACC}$	$ACC_{i,t-1} + \varepsilon_{i,t}$
Year	β^{EARN}	Adj. R ² _{EARN}	β^{CF}	Adj. R ² _{CF}	β^{ACC}	Adj. R ² _{ACC}
	(1)	(2)	(3)	(4)	(5)	(6)
1989	0.54	0.14	0.53	0.27	-0.29	0.07
1990	0.45	0.14	0.51	0.24	-0.21	0.03
1991	0.42	0.13	0.52	0.23	-0.17	0.02
1992	0.37	0.11	0.54	0.26	-0.20	0.04
1993	0.39	0.12	0.56	0.28	-0.21	0.04
1994	0.41	0.15	0.61	0.32	-0.16	0.02
1995	0.39	0.13	0.54	0.29	-0.22	0.04
1996	0.46	0.16	0.57	0.25	-0.12	0.01
1997	0.49	0.23	0.61	0.33	-0.09	0.01
1998	0.41	0.18	0.62	0.35	-0.13	0.01
1999	0.44	0.23	0.60	0.33	-0.03	0.00
2000	0.56	0.23	0.69	0.29	0.04	0.00
2001	0.38	0.22	0.58	0.31	0.05	0.00
2002	0.33	0.22	0.63	0.37	0.07	0.01
2003	0.45	0.31	0.67	0.41	0.07	0.00
2004	0.60	0.34	0.75	0.48	-0.17	0.01
2005	0.56	0.32	0.69	0.43	-0.10	0.01
2006	0.60	0.34	0.75	0.47	-0.10	0.00
2007	0.54	0.32	0.65	0.41	-0.03	0.00
2008	0.53	0.29	0.64	0.38	-0.11	0.01
2009	0.31	0.19	0.58	0.33	0.03	0.00
2010	0.44	0.24	0.64	0.37	-0.06	0.00
2011	0.54	0.28	0.71	0.38	-0.07	0.00
2012	0.63	0.36	0.79	0.50	-0.13	0.01
2013	0.54	0.31	0.79	0.47	-0.06	0.00
2014	0.63	0.42	0.79	0.53	-0.03	0.00
2015	0.54	0.37	0.74	0.51	-0.01	0.00
Average		0.24		0.36		0.01
Trend		0.010***		0.010***		-0.002***
(t-value)		[8.39]		[8.27]		[-5.56]

Panel B: Cash Flow Statement based approach

Table A12 presents results of regressions, estimated annually, of current operating cash flows on lagged earnings, accruals, and cash flows for the period 1989-2015, after excluding firm-year observations corresponding to the following non-articulating events: mergers and acquisitions, divestitures, foreign currency translations.

Panel A (B) presents results where accruals and cash flows are computed using a balance sheet (cash flow statement) based approach

 β^{EARN} and Adj. R^{2}_{EARN} are the coefficient estimate and explanatory power, respectively, of the following regression model estimated by year:

$$CF_{i,t} = \beta_0 + \beta^{\text{EARN}} EARN_{i,t-1} + \varepsilon_{i,t}$$

 β^{CF} and Adj. R^2_{CF} are the coefficient estimate and explanatory power, respectively, of the following regression model estimated by year:

$$CF_{i,t} = \beta_0 + \beta^{CF} CF_{i,t-1} + \varepsilon_{i,t}$$

 β^{ACC} and Adj. R^{2}_{ACC} are the coefficient estimate and explanatory power, respectively, of the following regression model estimated by year:

$$CF_{i,t} = \beta_0 + \beta^{ACC} ACC_{i,t-1} + \varepsilon_{i,t}$$

Trend is the coefficient estimate obtained by regressing yearly estimates (Adj. R^2) obtained from each specification above on the time variable. *Average* is average explanatory power over the sample period. All other variables are described in Table 2 of the paper. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels (two-tailed p-values), respectively.

Fama-French 10 industries	Average		Time Trend	
Industry	Adj. R ² _{EARN}	Adj. R ² _{CF}	Adj. R^{2}_{EARN}	Adj. R ² _{CF}
	(1)	(2)	(3)	(4)
Non-Durables	0.21	0.27	0.005**	0.011***
Durables	0.21	0.28	0.012***	0.010***
Manufacturing	0.21	0.28	0.005***	0.003*
Energy	0.17	0.37	-0.000	0.007**
High Tech	0.24	0.35	0.011***	0.012***
Telecom	0.32	0.57	-0.007***	-0.002
Shops	0.19	0.30	0.011***	0.010***
Health	0.39	0.44	0.009***	0.006***
Utilities	0.13	0.19	0.003*	0.009***
Other	0.18	0.36	0.004***	0.007***

Table A13: Industry analysis

Table A13 reports average explanatory power and time trends in cash-flow predictability of earnings and cash flows after categorizing firms based on Fama-French 10-Industry classification for the sample period 1989-2015.

Adj. R^{2}_{EARN} is the mean explanatory power of the following regression model estimated by year for each industry: $CF_{i,t}$ (or $CF_{i,t+1}$) = $\beta_0 + \beta^{EARN} EARN_{i,t-1} + \varepsilon_{i,t}$,

Adj. \mathbb{R}^{2}_{CF} is the mean explanatory power of the following regression model estimated by year for each industry: $CF_{i,t}$ (or $CF_{i,t+1}$) = $\beta_{0} + \beta^{CF}CF_{i,t+1} + \varepsilon_{i,t}$

Time Trend is the coefficient estimate obtained by regressing yearly estimates (Adj. R²) obtained from each specification above for each industry on the time variable. All other variables are described in Table 2 of the paper. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels (two-tailed p-values), respectively.

Year	Adj. R ² _{ACC_COMP}	Adj. R ² _{CF, ACC_COMP}	Inc. R ² : ACC_COMP	Inc. R ² : CF
	(1)	(2)	(3)	(4)
1989	0.17	0.30	0.04	0.14
1990	0.16	0.27	0.03	0.12
1991	0.15	0.26	0.02	0.11
1992	0.11	0.27	0.01	0.16
1993	0.12	0.29	0.01	0.17
1994	0.09	0.33	0.01	0.24
1995	0.11	0.30	0.02	0.19
1996	0.06	0.28	0.04	0.22
1997	0.04	0.36	0.03	0.31
1998	0.07	0.36	0.01	0.28
1999	0.04	0.35	0.02	0.30
2000	0.04	0.31	0.02	0.28
2001	0.02	0.33	0.02	0.31
2002	0.10	0.39	0.02	0.29
2003	0.15	0.43	0.03	0.28
2004	0.15	0.49	0.01	0.34
2005	0.10	0.45	0.02	0.35
2006	0.13	0.49	0.02	0.36
2007	0.08	0.44	0.03	0.35
2008	0.08	0.41	0.03	0.33
2009	0.10	0.35	0.02	0.25
2010	0.12	0.40	0.03	0.28
2011	0.09	0.41	0.02	0.31
2012	0.12	0.53	0.02	0.40
2013	0.14	0.48	0.01	0.34
2014	0.12	0.56	0.03	0.45
2015	0.08	0.52	0.02	0.44
Average	0.10	0.38	0.02	0.28
Trend	-0.0004	0.0096***	-0.0000	0.0099***
(t-value)	[-0.37]	[8.47]	[-0.01]	[8.66]

Table A14: Disaggregating accruals based on financial statement source

Table A14 reports explanatory power of regression, estimated annually, of current operating cash flows on lagged accrual components and lagged cash flows for the period 1989-2015. Accrual components are estimated based on financial statement source as described in Casey et al. (2017).

Adj. $R^{2}_{ACC_COMP}$ (Adj. R^{2}_{CF,ACC_COMP}) is the explanatory power of the following regression model after excluding (including) current cash flows as an explanatory variable, estimated by year: $CF_{i,t} = \beta_0 + \beta^{ACC_CF} ACC_CF_{i,t-1} + \beta^{ACC_OE} ACC_OE_{i,t-1} + \beta^{ACC_BS} ACC_BS_{i,t-1} + \beta^{CF} CF_{i,t-1+\varepsilon_{i,t}}$

ACC_CF (ACC_OE, ACC_BS) refers to accruals based on cash flow statement (shareholder equity, balance sheet) as the source (Casey et al., 2017). Inc.R²: ACC_COMP (measured as Adj. R²_{CF, ACC_COMP} - Adj. R²_{CF}) refers to the incremental explanatory power of all lagged accrual components for predicting current cash flows. Inc. R²: CF

(measured as Adj. R^2_{CF, ACC_COMP} - Adj. $R^2_{ACC_COMP}$) refers to the incremental explanatory power of lagged cash flows for predicting current cash flows. *Trend* is the coefficient estimate obtained by regressing yearly estimates (Adj. R^2 /Inc. R^2) obtained from the specification above on the time variable. *Average* is average explanatory power over the sample period. All other variables are described in Table 2 of the paper. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels (two-tailed p-values), respectively.

Table A15: Cash flow predictability over time: Macroeconomic conditions

Panel A: Cash flow predictability over business cycles

Business Cycle	Adj. R ² _{EARN}	Adj. R ² _{CF}
Recession	0.19	0.30
Expansion	0.25	0.38

Panel B: Cash flow predictability over economic policy uncertainty periods

Macroeconomic Uncertainty	Adj. R^{2}_{EARN}	Adj. R ² _{CF}
High	0.22	0.33
Low	0.26	0.39

Table A15 presents results of regressing current operating cash flows on lagged earnings and cash flows for the alternative aggregate partitions. In Panel A (B) explanatory power is estimated for alternative business cycle (economic policy uncertainty) partitions. Business cycle classifications are from NBER.¹ Economic policy uncertainty is the average annual (monthly average) economic policy uncertainty index from Baker et al., 2016.² Periods with above (below) sample median policy uncertainty index are classified as high (low) macroeconomic uncertainty.

Adj. R^{2}_{EARN} is the explanatory power of the following regression model estimated by year: $CF_{i,t} = \beta_{0} + \beta^{EARN} EARN_{i,t-1} + \varepsilon_{i,t}$

Adj. R^{2}_{CF} is the explanatory power of the following regression model estimated by year: $CF_{i,t} = \beta_{0} + \beta^{CF} CF_{i,t-1} + \varepsilon_{i,t}$

All other variables are described in Table 2.

¹ Data are obtained from: <u>https://fred.stlouisfed.org/series/USREC</u>

² Data are obtained from: <u>http://www.policyuncertainty.com/us_monthly.html</u>