Rev Account Stud (2009) 14:358–391
DOI 10.1007/s11142-009-9086-7

Are analysts' earnings forecasts more accurate when accompanied by cash flow forecasts?

Andrew C. Call · Shuping Chen · Yen H. Tong

Published online: 21 February 2009

Abstract We examine whether analysts' earnings forecasts are more accurate when they also issue cash flow forecasts. We find that (i) analysts' earnings forecasts issued together with cash flow forecasts are more accurate than those not accompanied by cash flow forecasts, and (ii) analysts' earnings forecasts reflect a better understanding of the implications of current earnings for future earnings when they are accompanied by cash flow forecasts. These results are consistent with analysts adopting a more structured and disciplined approach to forecasting earnings when they also issue cash flow forecasts. Finally, we find that more accurate cash flow forecasts decrease the likelihood of analysts being fired, suggesting that cash flow forecast accuracy is relevant to analysts' career outcomes.

Keywords Analysts · Earnings forecasts · Cash flow forecasts · Forecast accuracy · Analyst turnover

JEL Classification G24 · G29 · M41

A. C. Call
J.M. Tull School of Accounting, Terry College of Business, University of Georgia, Athens, GA, USA
e-mail: andycall@uga.edu

S. Chen (✉)
McCombs School of Business, University of Texas, Austin, TX, USA
e-mail: Shuping.Chen@mccombs.utexas.edu

Y. H. Tong
Nanyang Business School, Nanyang Technological University, Singapore, Singapore
e-mail: ayhtong@ntu.edu.sg

1 Introduction

In the 1990s, analysts started to provide operating cash flow forecasts in addition to earnings forecasts and stock recommendations through financial information service companies (DeFond and Hung 2003).[1] We argue that when analysts forecast cash flows, they adopt a structured approach to forecasting, which includes forecasting a full set of financial statements—the income statement, the balance sheet and the cash flows statement. This approach to forecasting imposes greater discipline on the earnings forecast, as articulation of the three financial statements is required. In addition, when analysts forecast a full set of financial statements, they are more likely to pay attention to individual earnings components (for example, cash flow from operations and changes in working capital). Accordingly, we expect that when analysts issue cash flow forecasts in addition to earnings forecasts, they do a more thorough job of analyzing the firm's financial statements and achieve a better understanding of the firms' earnings components. As such, we examine whether earnings forecasts are more accurate when analysts also issue cash flow forecasts relative to when they only issue earnings forecasts.

This study has important implications for investors, academics, and analysts. Both earnings and cash flows are primitive accounting inputs for firm valuation (Francis et al. 2005; Chen et al. 2007), and analysts' earnings forecasts are used by investors in evaluating firm performance, forming earnings expectations and setting stock prices (Brown 1993; Park and Stice 2000; Gleason and Lee 2003; Clement and Tse 2003). Hence, investors can benefit from more accurate earnings forecasts in their investment decisions (Loh and Mian 2006), and a simple heuristic to identify analyst forecasts that are more accurate (such as whether the analyst issues a cash flow forecast) can greatly reduce investors' information search costs.[2] Academic researchers also rely extensively on analyst forecasts in studies covering such topics as earnings management, the pricing of accounting information, and cost of capital (for example, Ettredge et al. 1995; Dechow et al. 1999; Degeorge et al. 1999; Skinner and Sloan 2002; Matsumoto 2002; Burgstahler and Eames 2003; Easton and Monahan 2005). A better understanding of the determinants of forecast accuracy enables researchers to generate more accurate proxies for expected future earnings and lends more credibility to research findings. Earnings forecast accuracy is also of concern to analysts because their career prospects and rewards are affected by forecast accuracy (Mikhail et al. 1999; Hong and Kubik 2003).[3]

We compare the accuracy of earnings forecasts issued with and without cash flow forecasts. To triangulate our results, we employ multiple empirical approaches.

[1] Hereafter, we use operating cash flows and cash flows interchangeably to refer to cash flows from operations.

[2] Loh and Mian (2006) provide evidence consistent with individual analysts using their earnings forecasts to produce stock recommendations, with more accurate forecasters providing more profitable recommendations.

[3] See Schipper (1991), Brown (1993) and Ramnath et al. (2008) for literature reviews on research related to analyst' forecasts and stock recommendations.

First, in a univariate analysis at the firm level, we directly compare the average earnings forecast accuracy of analysts who issue cash flow forecasts with the average earnings forecast accuracy of analysts who do not issue cash flow forecasts. We find earnings forecasts of analysts who also issue cash flow forecasts are on average 10% more accurate than are those of analysts following the same firm who do not issue cash flow forecasts. Second, using regression analysis at the analyst level, we examine the relative accuracy of earnings forecasts based on three distinct specifications: (i) pooled regression across all earnings forecasts, (ii) analyst-specific regressions examining the earnings forecast accuracy of analysts who issue cash flow forecasts for some firms but not for others, and (iii) changes regressions focusing on improvements (deterioration) in earnings forecast accuracy when analysts start (stop) issuing cash flow forecasts for a firm. Depending on the specification, we find that relative to earnings forecasts issued in isolation, analysts' earnings forecasts accompanied by cash flow forecasts are on average 0.6–5.0% more accurate than the *mean* earnings forecast of *all* analysts following the firm, after controlling for other factors affecting earnings forecast accuracy. Our results support the hypothesis that the issuance of cash flow forecasts is positively associated with earnings forecast accuracy.

In addition, we directly investigate the validity of our assumption that when analysts issue cash flow forecasts, they obtain a better understanding of the time-series properties of the earnings components. We test this assumption by examining whether earnings forecasts issued along with cash flow forecasts better reflect the implications of current cash flows and accruals for future earnings than do earnings forecasts issued in isolation. We find evidence consistent with this assumption. Specifically, we find analysts' under-estimation of the persistence of accruals and cash flows is mitigated by approximately 30% when they issue cash flow forecasts relative to when they only issue earnings forecasts. Thus, the process of forecasting a full set of financial statements and issuing a cash flow forecast leads to significant improvement in the analysts' understanding of the time series properties of earnings.

With regard to analysts' career outcomes, we document evidence that brokerages base their firing decisions on both cash flow forecast accuracy and earnings forecast accuracy. Specifically, after controlling for earnings forecast accuracy, bias, and boldness (Mikhail et al. 1999; Ke and Yu 2006), we find that (i) analysts who issue cash flow forecasts together with earnings forecasts are less likely to be fired and that (ii) analysts who issue relatively more accurate cash flow forecasts are less likely to be fired than analysts who issue less accurate cash flow forecasts. Thus, in the presence of cash flow and earnings forecasts, brokerages use both pieces of information in their firing decisions, and more accurate cash flow forecasters are less likely to be fired.

Our study should be of interest to both academics and capital market participants and contributes to the extant accounting literature in the following ways. First, we add to the recent accounting literature on the effects of cash flow forecasts provided by analysts. Recent studies focus on either the determinants of market participants' demand and analysts' supply of cash flow forecasts (DeFond and Hung 2003; Ertimur and Stubben 2005) or the impact of cash flow forecasts on investors' pricing and managers' reporting of earnings (McInnis and Collins 2008; Call 2008). Our study takes a different perspective and examines the effects of cash flow forecast issuance on the quality of analysts' own research output (i.e., the accuracy of their earnings forecasts) and their career outcomes. As such, we contribute to the emerging literature on the impact of analysts' cash flow forecasts.

Second, Hirshleifer and Teoh (2003) predict that when the components of aggregated information exhibit different time-series properties and forecasting effort is concentrated on the individual components instead of the aggregated information, the resulting forecast of the aggregated information is more accurate. Using an experiment, Hewitt (2008) finds that when the earnings components are differentially persistent, earnings forecast accuracy is enhanced when participants are required to attend to the individual earnings components. Our study complements and extends Hewitt's (2008) experimental results by providing large sample evidence consistent with Hirshleifer and Teoh's (2003) theoretical prediction. Our paper is also closely related to concurrent papers by Pae et al. (2007) and Ertimur et al. (2008). However, our analysis differs from both papers in important aspects. We examine two issues that are not investigated in Pae et al. (2007). Specifically, we provide evidence that when analysts issue cash flow forecasts, they better understand the implications of the cash flow and accrual components of current earnings for future earnings. We also document that analysts with better cash flow forecast accuracy are less likely to be fired by their employers. We differ from Ertimur et al. (2008) as their focus is on analysts' choice to disseminate their private revenue forecasts, while our focus, in contrast, is on the impact of forecasting cash flows on the quality of analysts' research output, namely, earnings forecast accuracy, and their career outcomes.

The rest of the paper is organized as follows. The next section reviews relevant literature and develops our predictions. Section 3 describes our sample and measurement of earnings forecast accuracy. Sections 4, 5 and 6 present the research designs to test our three hypotheses and their respective results. Section 7 presents results of sensitivity analyses. Section 8 concludes.

2 Background and hypothesis development

The issuance of operating cash flow forecasts by analysts is a relatively recent phenomenon. As documented by DeFond and Hung (2003), analysts' cash flow forecasts first appear in the *I/B/E/S* database in 1993. At the firm level, the percentage of US firms in the *I/B/E/S* database with at least one cash flow forecast issued by analysts increased from 4% in 1993 to 54% in 2005. This growth trend in cash flow forecast issuance is also observed at the analyst level. Specifically, the percentage of analysts' earnings forecasts that are accompanied by cash flow forecasts has increased from 1% in 1993 to 32% in 2005.

Two main areas of research have emerged on analysts' cash flow forecasts. The first focuses on the firm specific and analyst specific determinants of analysts' issuance of cash flows forecasts (DeFond and Hung 2003; Ertimur and Stubben 2005). DeFond and Hung (2003) report that, relative to firms without cash flow forecasts, firms that have both cash flow and earnings forecasts have larger accruals, higher earnings volatility, greater capital intensity, higher market values of equity, poorer financial health and greater accounting choice heterogeneity relative to industry peers. Ertimur and Stubben (2005) examine whether analyst characteristics play a role in the supply of cash flow forecasts. They find analysts from bigger brokerage houses, who forecast earnings more frequently and who have less accurate prior earnings forecasts, are more likely to issue cash flow forecasts.

The second area focuses on the impact of cash flow forecasts on investors and managers (DeFond and Hung 2003; McInnis and Collins 2008; Call 2008). Using long-window returns, both DeFond and Hung (2003) and Call (2008) examine whether investors respond differently to the cash flow and accrual components of earnings when setting stock prices for firms with cash flow forecasts. These studies provide joint evidence indicating that investors place relatively more (less) weight on the cash (accrual) component of earnings for firms whose analysts issue cash flow forecasts than for firms whose analysts do not. In addition, DeFond and Hung (2003) examine the two-day abnormal returns surrounding firms' announcement of earnings. For firms with cash flow forecasts, they find no significant relation between unexpected earnings and abnormal returns but a strong positive relation between unexpected cash flows and abnormal returns. This result contrasts with the strong positive relation between abnormal returns and earnings for firms without cash flow forecasts. In examining managerial response to cash flow forecasts, McInnis and Collins (2008) predict that cash flow forecasts increase the transparency of accrual manipulations because cash flow forecasts enable market participants to decompose earnings surprises into their cash flow and accrual components. They find firms with cash flow forecasts are less likely to manipulate reported earnings relative to firms without cash flow forecasts, resulting in better accruals quality and a decreased likelihood of meeting earnings targets. In addition, Call (2008) finds that cash flow forecasts discipline managers to report more informative operating cash flows. Thus, existing research indicates that analysts' cash flow forecasts have important implications for both investors and managers.

While prior studies examine the determinants of analysts' issuance of cash flow forecasts and the impact of such forecasts on investors and managers, our research takes a different perspective and examines the impact of issuing cash flow forecasts on analysts' own research output and on their career outcomes. Both *I/B/E/S* documentation and DeFond and Hung (2003) make explicit the point that cash flow forecasts provided by analysts are not simply mechanical manipulations of earnings (i.e., earnings before interest, tax, depreciation and amortization). DeFond and Hung (2003) examine several full-text reports by *I/B/E/S* contributing analysts and find evidence that analysts base their cash flow forecasts on sophisticated procedures involving the prediction of items such as working capital and deferred taxes. Our own detailed reading of multiple analyst reports containing cash flow forecasts (obtained from Investext) leads to the same inference as in DeFond and Hung

(2003). We find analysts forecast several balance sheet items when forecasting operating cash flows. For example, analysts provide specific estimates of accounts receivable, accounts payable, inventories, deferred taxes and depreciation in order to derive operating cash flow estimates from their earnings forecasts.[4] Therefore, we conjecture that when analysts forecast cash flows, they are also forecasting a full set of financial statements—the income statement, the balance sheet and the cash flows statement. This structured approach to forecasting financial statements imposes discipline on the earnings forecasts and facilitates a better understanding of the firms' earnings process.[5]

In addition, Hirshleifer and Teoh (2003) argue that, to achieve greater forecast accuracy in the presence of components of aggregated information with differential growth rates (i.e., different levels of persistence), forecasters should attend to the disaggregated components instead of focusing on just the aggregated information. They illustrate their argument using an analytical model examining earnings forecast accuracy when the firm's business segments are growing at different rates (i.e., business segment earnings are differentially persistent). They show that when forecasting efforts are focused on aggregated earnings rather than segment earnings, the resulting forecast of earnings is relatively less accurate. In our setting, the Hirshleifer and Teoh (2003) framework suggests that when analysts forecast the components of earnings (for example, cash flow from operations and changes in working capital), they are likely to have more accurate forecasts of earnings, relative to when they only forecast aggregate earnings.[6]

Based on the above discussion, we expect that when analysts forecast both cash flows and earnings, they adopt a more disciplined approach to forecasting. Thus they are likely to achieve a better understanding of the firms' earnings process. Following this logic, we expect better earnings forecast accuracy when analysts simultaneously issue cash flow and earnings forecasts relative to when they only issue earnings forecasts.[7] We test the following hypothesis:

[4] In a recent working paper, Givoly et al. (2008) examine the properties of analysts' cash flow forecasts and raise concerns about this assumption. They find that in a regression of cash flow forecasts on earnings forecasts, depreciation expense, working capital accruals, and other accrual adjustments, the coefficients on the earnings forecasts and depreciation expense approach 1.0, whereas the coefficients on working capital accruals and other accrual adjustments, although positive, are very small (0.06). They thus conclude that analysts' cash flow forecasts appear to be simple, mechanical adjustments to their own earnings forecasts. This is not consistent with both DeFond and Hung's (2003) conclusion and our own readings of analyst research reports.

[5] As discussed in Lundholm and Sloan (2007), forecasting a full set of financial statements allows analysts to fully consider the firms' interacted set of operating, investing, and financing activities. For example, the forecast of interest expense on the income statement is dependent of the amount of debt forecasted on the balance sheet. The amount of forecasted debt is dependent on the forecast of the firm's net operating assets and capital structure. In turn, the forecast of net operating assets depends on the forecast of sales growth. This structured approach to forecasting imposes discipline on the earnings forecasts and facilitates analysts' understanding of the firms' business and earnings processes.

[6] The accounting literature indicates that the cash flow and accrual components of earnings exhibit different time-series properties (Sloan 1996; Xie 2001; Call et al. 2008).

[7] DeFond and Hung (2003) find that analysts are more likely to issue cash flow forecasts for firms with low quality earnings (e.g., higher earnings volatility and greater heterogeneity of accounting choice). Assuming analysts place more emphasis on forecasting cash flows than on forecasting earnings, this could

H1 Analysts' earnings forecasts are more accurate when they are accompanied by cash flow forecasts.

An important assumption underlying H1 is that when analysts issue both cash flow and earnings forecasts, they achieve a better understanding of the firms' earnings components. We directly examine whether this assumption is valid by focusing on analysts' understanding of the persistence of accruals and cash flows as reflected by their earnings forecasts. Existing studies provide evidence that is generally consistent with analysts' inefficient processing of information. For example, Rajgopal et al. (2003), Ahmed et al. (2006) and Yu (2007) find evidence indicating that analysts underestimate the persistence of earnings. Ahmed et al. (2006) and Yu (2007) further document that analysts underweight the implications of the cash flow and accrual components of current earnings for future earnings.[8] We conjecture that, relative to instances when analysts issue only earnings forecasts, they achieve a better understanding of the time-series properties of the components of earnings when they issue both cash flow and earnings forecasts. Thus, we expect *less* underweighting of the persistence of the cash flow and accrual components of earnings when analysts issue both cash flow and earnings forecasts:

H2 The earnings expectations embedded in analysts' forecasts better reflect the persistence of the cash flow and accrual components of current earnings when analysts issue both cash flow and earnings forecasts relative to when they only issue earnings forecasts.

Finally, we examine whether analysts' career outcomes are affected by cash flow forecast accuracy. Findings in DeFond and Hung (2003) and Call (2008) suggest that investors price cash flows differently for firms with a cash flow forecast. It is therefore likely that brokerages also use cash flow forecasts in their firing decisions. Prior research also documents that brokerages base their firing decisions, in part, on analysts' earnings forecast accuracy (Mikhail et al. 1999). Among analysts who issue both cash flow and earnings forecasts, brokerages have potentially two performance indicators (i.e., cash flow forecast accuracy and earnings forecast accuracy) upon which to base their firing decisions. As a result, we make the following prediction:

Footnote 7 continued
result in a negative association between the presence of cash flow forecasts and earnings forecast accuracy, inconsistent with our prediction. However, there is no empirical evidence that supports the above assumption. Moreover, in their long-run stock returns analysis, DeFond and Hung (2003) find that investors place greater weight on earnings compared to cash flows for all firms (i.e., regardless of the presence of analysts' cash flow forecasts), suggesting that earnings information continues to be of primary importance even for firms with cash flow forecasts.

[8] Elgers et al. (2003) and Bradshaw et al. (2001) find evidence consistent with analysts' overreaction to the implication of current accruals for future earnings. However, in their analyses they examine analysts' reaction to accrual information without controlling for cash flows. In contrast, Ahmed et al. (2006) and Yu (2007) jointly consider the implications of accruals and cash flows for future earnings and find analysts underreact to the implications of both accruals and cash flows for future earnings.

H3 Among analysts who simultaneously issue both cash flow and earnings forecasts, those with relatively less accurate cash flow forecasts are more likely to be fired.

3 Sample and measurement of earnings forecast accuracy

3.1 Sample

We obtain analyst data from the *I/B/E/S Detail History US Edition* database for the period 1993–2005. We begin by identifying all firms with one-year ahead annual earnings forecasts and with at least one analyst cash flow forecast. Restricting the sample to those firms with at least one cash flow forecast allows us to abstract away from firm characteristics and instead focus on controlling analyst-specific characteristics that affect earnings forecast accuracy.[9,10]

We focus on annual earnings forecasts because cash flow forecasts on *I/B/E/S* are mostly annual forecasts.[11] For each analyst-firm-year observation, we use the most recent earnings and cash flow forecasts prior to the announcement of earnings. We winsorize all continuous dependent and independent variables at the 1% and 99% levels. Based on our sample criteria, we obtain 380,680 analyst-firm-year observations with 26,184 unique analysts and 15,503 unique firms for our primary test of the impact of cash flow forecast issuance on earnings forecast accuracy. Since sample sizes differ for different tests due to various research designs and data requirements, we report the sample sizes in all our tables for ease of reading.

3.2 Measurement of analyst-level earnings forecast accuracy

To measure earnings forecast accuracy at the *analyst level*, we calculate the absolute forecast error (FE_{ijt}) as the absolute difference between the analyst's forecast of

[9] The only exception to this sampling requirement is our test using analyst-specific regressions: since we examine the difference in earnings forecast accuracy for the same analyst who gives cash flow forecasts for some firms but not others, we include firms that have no cash flow forecasts in our sample. Our results are robust to restricting this sample to only those firm-years with at least one cash flow forecast. Please see Sect. 4.2 for more details.

[10] Our sample differs from the sample employed in Pae et al. (2007) in that we do not restrict our sample of *I/B/E/S* analyst-firm observations to firms that are also on Compustat. Restricting the sample to firms on Compustat results in a much smaller sample of primarily larger firms, impacting both the inference and generalizability of the research findings.

[11] We identify analysts who simultaneously issue cash flow forecasts and earnings forecasts and analysts who only issue earnings forecasts from the *I/B/E/S* database. Our communication with *I/B/E/S* reveals that *I/B/E/S* does not impose any restrictions, except for standard quality assurances, on the types of analyst forecasts reported in its database (e.g., revenue, cash flow and earnings forecasts). That is, *I/B/E/S* will make available in its database all forms of forecasts provided by the analysts. Hence, we rely on *I/B/E/S* when determining whether an analyst issued a cash flow forecast for a particular firm. To the extent that analysts who only issue earnings forecasts to *I/B/E/S* also privately forecast cash flows, this will bias against finding results consistent with our predictions.

earnings and actual earnings for the year as reported by *I/B/E/S*. Consistent with Clement (1999), we then mean-adjust the absolute forecast errors.[12] We measure this mean-adjusted variable as follows:

$$MAFE_{ijt} = -1 \times \left(FE_{ijt} - \overline{FE}_{jt}\right)/\overline{FE}_{jt} \tag{1}$$

FE_{ijt} is analyst i's absolute earnings forecast error for firm j in year t, and $\overline{FE}_{jt}$ is the mean absolute forecast error across all analysts following firm j in year t. We multiply by negative one so that more positive (negative) values indicate that an analyst is more (less) accurate than the average analyst following the firm.

Consistent with prior studies, we use mean-adjusted absolute forecast errors to enable the comparison of analysts' earnings forecasts across firms and across time periods (Clement 1999; Jacob et al. 1999; Chen and Matsumoto 2006). This measure controls for variations in forecasting difficulty across firms and across years. For example, if earnings for firm A are more difficult to forecast than are earnings for firm B, this greater forecasting difficulty will affect all analysts following firm A, and a simple comparison of unadjusted absolute forecast errors would likely suggest that forecasts for firm A are less accurate than forecasts for firm B. Therefore, we control for the inherent difficulty in forecasting a firm's earnings by subtracting the mean forecast error for each firm and measuring earnings forecast accuracy relative to all analysts following the same firm in the same year. This mean-adjustment thus allows us to meaningfully compare the accuracy of earnings forecasts across analysts following different firms and in different years.

4 Are earnings forecasts more accurate when accompanied by cash flow forecasts?

4.1 Main empirical specification—pooled analysis

4.1.1 Empirical models

Using *MAFE* as our dependent variable and the following pooled regression, we examine whether earnings forecasts are more accurate when accompanied by cash flow forecasts:[13]

[12] Unlike Pae et al. (2007), who use range-adjusted forecast errors, we use mean-adjusted forecast errors for our relative earnings forecast accuracy measure. Prior studies that use range-adjusted forecast errors (e.g., Clement and Tse 2003, 2005; Brown and Hugon 2007) mainly do so to compare regression coefficients across two models—one that models earnings forecast accuracy and one that models market reactions to analysts' forecasts. Therefore, we mean-adjust because we do not model market reactions and because it facilitates comparison with other prior studies that also use mean-adjusted forecast errors (e.g., Clement 1999; Jacob et al. 1999; Chen and Matsumoto 2006).

[13] Unlike Pae et al. (2007), who use the Heckman (1979) two-stage self-selection model to control for the endogeneity of analysts' decision to issue cash flow forecasts, we include analyst-firm and analyst specific variables that have been identified in prior research to be associated with the issuance of cash flow forecasts directly into Eq. 2. We do this for two reasons. First, the same variables (e.g., lagged earnings forecasts accuracy, forecast frequency, and brokerage size) that affect analysts' decision to issue cash flows forecasts also affect earnings forecast accuracy. Therefore, it is difficult to impose the exclusion

$$
\begin{aligned}
MAFE_{ijt} = \alpha_{ijt} &+ \beta_1 CFF_{ijt} + \beta_2 LMAFE_{ijt} + \beta_3 MAGE_{ijt} + \beta_4 MFREQ_{ijt} \\
&+ \beta_5 MFEXP_{ijt} + \beta_6 MGEXP_{itj} + \beta_7 DTOP10_{it} + \beta_8 MNCOS_{ijt} \\
&+ \beta_9 MNSIC_{ijt} + YEAR + \varepsilon_{ijt}
\end{aligned} \tag{2}
$$

where $MAFE_{ijt}$ = as defined in Eq. 1; CFF_{ijt} = dummy variable set equal to 1 if analyst i issues both cash flow and earnings forecasts for firm j in year t, and set equal to zero if analyst i only issues earnings forecasts for firm j in year t; $LMAFE_{ijt}$ = one period lagged *MAFE*; $MAGE_{ijt}$ = mean-adjusted number of days between analyst i's earnings forecast date and the actual earnings announcement date for firm j in year t; $MFREQ_{ijt}$ = mean-adjusted number of distinct earnings forecasts made by analyst i for firm j in year t; $MFEXP_{ijt}$ = mean-adjusted number of years for which analyst i has supplied at least one earnings forecast for firm j, prior to year t; $MGEXP_{ijt}$ = mean-adjusted number of years for which analyst i has supplied at least one earnings forecast, prior to year t; $DTOP10_{it}$ = dummy variable set equal to 1 if analyst i is employed by a brokerage firm in the top size decile during year t, and set equal to 0 otherwise. Size deciles are based on the number of unique analysts employed in year t; $MNCOS_{it}$ = mean-adjusted number of distinct firms for which analyst i makes at least one earnings forecast during year t; $MNSIC2_{it}$ = mean-adjusted number of distinct industries (based on two-digit SIC codes) for which analyst i makes at least one forecast during year t; *YEAR* = year dummies.

To conform to the specification of the dependent variable (mean-adjustment), all the independent variables are also mean-adjusted except for the indicator variables *DTOP10* and *CFF*.[14] Consistent with H1, we expect the coefficient on *CFF* to be significantly positive.

In Eq. 2, we control for several analyst-firm specific (*LMAFE*, *MAGE*, *MFREQ*, *MFEXP*) and analyst specific (*MGEXP*, *DTOP10*, *MNCOS*, *MNSIC2*) variables that have been identified in prior research to be associated with earnings forecast accuracy and that may also be associated with the issuance of cash flow forecasts. To control for analyst-firm specific factors, we include one-period lagged mean-adjusted earnings forecast accuracy (*LMAFE*), as prior research finds that past

Footnote 13 continued
restriction in the Heckman (1979) two-stage approach which requires some variables to be included in the choice model (i.e., cash flows forecasts issuance model) that do not appear in the treatment model (i.e., earnings forecast accuracy model). If the exclusion restriction is not imposed, the resulting estimates in the treatment model are likely to be inefficient, leading to overstated standard errors (Wooldridge 2006). Note that Pae et al. (2007) do not account for this exclusion restriction as all the variables that appear in their choice model also appear in their treatment model. Second, Francis and Lennox (2008) suggest that in the presence of inappropriate model specifications, Heckman selection models can provide inferences that are extremely fragile and have severe multicollinearity problems. They show that virtually any possible inference is achievable in the second stage estimation with minor changes to model specification in either or both the choice and treatment models. As such, we do not rely on the Heckman procedure but employ two alternative empirical specifications to examine the relation between the issuance of cash flows forecasts and earnings forecast accuracy to mitigate the concerns over endogeneity of analysts' decision to issue cash flows forecast. These alternative specifications are discussed in Sects. 4.2 and 4.3.

[14] The results are unchanged when *DTOP10* is mean-adjusted.

earnings forecast accuracy is a determinant of current earnings forecast accuracy (Brown 2001) and that analysts are more likely to issue cash flow forecasts for a firm if their prior earnings forecast is relatively less accurate for that particular firm (Ertimur and Stubben 2005). We also include the mean-adjusted earnings forecast frequency (*MFREQ*) because existing evidence finds that earnings forecast accuracy is positively associated with forecast frequency (Jacob et al. 1999) and with the likelihood of cash flow forecast issuance (Ertimur and Stubben 2005). We control for the age of the earnings forecast (*MAGE*) as prior papers find forecast age is negatively associated with forecast accuracy (Brown et al. 1987; O'Brien 1988; Clement 1999). In addition, Clement (1999) finds analysts' firm-specific forecasting experience is associated with greater forecast accuracy. Hence, we include the mean-adjusted number of years the analyst has been making earnings forecasts for a particular firm to control for this effect (*MFEXP*).

Turning to analyst specific control variables, prior research finds that analysts with more experience issue more accurate earnings forecasts (Mikhail et al. 1997; Clement 1999). Consistent with Clement (1999), we include the mean-adjusted number of years the analyst has been making earnings forecasts to control for the analyst's general forecasting experience (*MGEXP*). Clement (1999) and Jacob et al. (1999) find that brokerage size is positively associated with forecast accuracy and argue that analysts employed by larger brokerages have more resources available to them. Furthermore, Ertimur and Stubben (2005) find analysts working at smaller brokerages are less likely to issue cash flow forecasts. As in Clement (1999), we include a dummy variable indicating the size of the brokerage to control for the availability of resources (*DTOP10*). In addition, Clement (1999) finds that forecast accuracy decreases with the number of companies and industries followed by the analyst. As a result, we include the mean-adjusted number of firms followed by the analyst (*MNCOS*) and the mean-adjusted number of industries followed by the analyst (*MNSIC2*).[15]

Finally, we include year dummies (*YEAR*) to control for cross-sectional dependence. The same analysts likely appear multiple times in our sample and earnings forecast properties might persist over time. In such a case, the traditional *t*-statistics can be inflated. Thus we calculate analyst-clustered standard errors to control for time-series dependence in earnings forecast accuracy (Petersen 2009).

4.1.2 Empirical results

4.1.2.1 Descriptive statistics and univariate analysis In Table 1 we present descriptive statistics separately for earnings forecasts issued with and without cash flow forecasts. We report raw values in Panel A (to facilitate a more intuitive

[15] One concern is that the issuance of cash flow forecasts simply identifies firms that analysts care more about and on which they expend more forecasting efforts. Clement et al. (2003) measure analyst effort using earnings forecast frequency, as analysts who work harder analyzing a firm generate more forecasts for that firm. Barth et al. (2001) use the number of firms followed by the analyst to proxy for analysts' effort, as the fewer firms an analyst follows, the greater the effort spent on each firms. Our inclusion of *MFREQ* and *MNCOS* as control variables mitigates the concern of omitted correlated variables associated with analysts' efforts.

Table 1 Descriptive statistics on analyst earnings forecast characteristics

	Means		Medians		Tests of significance	
	Issuing	Non-issuing	Issuing	Non-issuing	Difference of means[a]	Difference of medians[b]
Panel A: Raw values						
AGE	138.195	159.031	109.000	126.000	<.001	<.001
FREQ	4.350	3.488	4.000	3.000	<.001	<.001
FEXP	1.226	1.393	1.000	1.000	<.001	<.001
GEXP	4.441	5.116	3.000	4.000	<.001	<.001
DTOP10	0.566	0.556	1.000	1.000	<.001	<.001
NCOS	16.165	18.231	13.000	14.000	<.001	<.001
NSIC2	1.557	2.201	1.000	1.000	<.001	<.001
N	171,944	208,736	171,944	208,736		
Panel B: Mean-adjusted values						
MAGE	−0.010	0.140	−0.133	−0.014	<.001	<.001
MFREQ	0.205	0.028	0.125	−0.042	<.001	<.001
MFEXP	−0.321	−0.311	−0.455	−0.475	<.001	0.042
MGEXP	0.196	0.218	0.000	0.021	<.001	<.001
DTOP10	0.566	0.556	1.000	1.000	<.001	<.001
MNCOS	0.035	0.061	−0.048	−0.061	<.001	<.001
MNSIC2	−0.008	0.005	0.000	0.000	<.001	<.001
MAFE	0.034	−0.044	0.165	0.132	<.001	<.001
N	171,944	208,736	171,944	208,736		

	N	Mean	Median
Panel C: Earnings forecast errors of analysts who issue cash flow forecasts versus analysts who only issue earnings forecasts			
EFE-CFF	14,463	0.399	0.096
EFE-NoCFF	14,463	0.446	0.109
Difference	14,463	−0.047***	−0.008***
Panel D: Earnings forecast errors partitioned by analyst following			
Small firms (mean analyst following = 15.2)			
EFE-CFF	5,063	0.389	0.086
EFE-NoCFF	5,063	0.431	0.099
Difference	5,063	−0.042***	−0.008***
Medium firms (mean analyst following = 21.7)			
EFE-CFF	4,744	0.407	0.099
EFE-NoCFF	4,744	0.451	0.112
Difference	4,744	−0.044***	−0.008***
Large firms (mean analyst following = 33.4)			
EFE-CFF	4,656	0.401	0.101

Table 1 continued

	N	Mean	Median
EFE-NoCFF	4,656	0.456	0.116
Difference	4,656	−0.055***	−0.009***

We report two-sided p-values. All variables are winsorized at the 1% and 99% levels

[a] p-Values are associated with t-statistics. When tests indicate inequality of variances at the 10% level, we report t-statistics that assume unequal variances. Otherwise, we report t-statistics that assume equal variances

[b] p-Values are associated with Wilcoxon z-statistics

Definition of variables:

Panel A: *AGE* = age (in days) of analyst i's forecast for firm j's earnings at time t; *FREQ* = number of forecasts issued by analyst i for firm j's earnings in year t; *FEXP* = number of years through year t for which analyst i supplied at least one earnings forecast for firm j; *GEXP* = number of years through year t for which analyst i supplied at least one earnings forecast; *DTOP10* = a dummy variable set to 1 if analyst i is employed by a firm in the top size decile during year t, and set to 0 otherwise. Size deciles are calculated based on the number of analysts employed in year t; *NCOS* = number of firms for which analyst i supplied at least one earnings forecast in year t; *NSIC2* = number of two-digit SICs for which analyst i supplied at least one earnings forecast in year t

Panel B: *MAGE* = age (in days) of analyst i's earnings forecast for firm j's earnings at time t minus the age of the average analyst's earnings forecast following firm j in year t, scaled by the age of the average analyst's earnings forecast following firm j in year t; *MFREQ* = number of forecasts issued by analyst i for firm j's earnings in year t minus the average number of forecasts issued for firm j in year t scaled by the average number of forecasts issued for firm j in year t; *MFEXP* = number of years through year t for which analyst i supplied at least one earnings forecast for firm j minus the average number of years analysts following firm j had supplied earnings forecasts through year t scaled by the average number of years analysts following firm j had supplied earnings forecasts through year t; *MGEXP* = number of years through year t for which analyst i supplied at least one earnings forecast minus the average number of years through year t analysts supplied at least one earnings forecast scaled by the average number of years through year t analysts supplied at least one earnings forecast; *DTOP10* = a dummy variable set to 1 if analyst i is employed by a firm in the top size decile during year t, and set to 0 otherwise. Size deciles are calculated based on the number of analysts employed in year t; *MNCOS* = number of firms for which analyst i supplied at least one earnings forecast in year t minus the average number of firms followed by an analyst following firm j in year t scaled by the average number of firms followed by an analyst following firm j in year t; *MNSIC2* = number of two-digit SICs for which analyst i supplied at least one earnings forecast in year t minus the average number of two-digit SICs followed by an analyst following firm j at time t scaled by the average number of two-digit SICs followed by an analyst following firm j at time t; *MAFE* = mean-adjusted absolute earnings forecast error, calculated as the difference between the absolute earnings forecast error for analyst i for firm j in year t and the mean absolute earnings forecast error for firm j in year t scaled by the mean absolute earnings forecast error for firm j in year t

Panels C and D: *EFE-CFF* = the consensus absolute earnings forecast error for all analysts who accompany their earnings forecasts with a cash flow forecast. For each firm-year, we measure the consensus absolute earnings forecast error as the absolute difference between the consensus forecast of earnings and actual earnings (forecast minus actual), scaled by the absolute value of the firm's actual earnings; *EFE-NoCFF* = the consensus absolute earnings forecast error for all analysts who do not accompany their earnings forecasts with a cash flow forecast. For each firm-year, we measure the consensus earnings forecast error as the absolute difference between the consensus forecast of earnings and actual earnings (forecast minus actual), scaled by the absolute value of the firm's actual earnings

understanding of the descriptive statistics) and mean-adjusted values in Panel B. Compared to earnings forecasts issued without cash flow forecasts, earnings forecasts issued with cash flow forecasts are issued more frequently (4.4 forecasts versus 3.5 forecasts per year), are associated with analysts who work for smaller brokerage houses, and who follow fewer firms and fewer industries (16 versus 18 firms, 1.6 versus 2.2 industries). The forecasting horizon tends to be shorter (138 versus 159 days) for earnings forecasts issued with cash flow forecasts. In addition, earnings forecasts issued with cash flow forecasts are associated with analysts who tend to have less general forecasting experience (4.4 versus 5.1 years) and less firm-specific forecasting experience (1.2 versus 1.4 years). All of the differences are statistically significant at both the mean and the median level. As shown in Panel B, the mean-adjusted forecast accuracy (*MAFE*) of earnings forecasts issued in conjunction with cash flow forecasts is higher than that of earnings forecasts issued without cash flow forecasts.[16] This univariate result is consistent with analysts demonstrating greater relative earnings forecast accuracy when they issue cash flows forecasts together with earnings forecasts.

To more directly compare the differential forecast accuracy when analysts issue cash flow forecasts compared to when they do not, we employ the following methodology. We first compute two consensus absolute earnings forecast errors for each firm in each year: one represents the consensus absolute earnings forecast error for all analysts who accompany their earnings forecast with a cash flow forecast, and the other represents the consensus absolute earnings forecast error for all analysts who only issue an earnings forecast. Consensus absolute earnings forecast accuracy is simply the absolute value of consensus earnings forecast minus actual earnings, scaled by the absolute value of actual earnings. Second, for each firm in each year, we calculate the difference in these consensus absolute earnings forecast errors across the group of analysts who issue cash flow forecasts (*EFE-CFF*) and the group of analysts who do not issue cash flow forecasts (*EFE-NoCFF*). Using this matched firm-year approach to control for firm and year differences in forecasting difficulty enables us to infer whether on average a given firm in a given year receives its most accurate earnings forecasts from those analysts who issue cash flow forecasts or from those analysts who do not. We require at least 10 earnings forecasts for each firm-year in this analysis, resulting in 14,463 firm-year observations that have both earnings and cash flow forecasts.

As reported in Panel C of Table 1, we find the mean (median) consensus absolute forecast error of analysts who also issue cash flow forecasts is 0.399 (0.096) compared to 0.446 (0.109) for analysts who only issue earnings forecasts. The mean (−0.047) and median (−0.008) difference in these consensus absolute earnings forecast errors is statistically significant at the 1% level. This result suggests the consensus earnings forecasts of analysts who also issue cash flow forecasts are on average about 10% more accurate than those of the analysts who forecast only earnings. In addition, we partition the sample into three groups based on the number

[16] Note that we mean adjust forecast errors with respect to *all* analysts issuing earnings forecasts for firm j in year t. However, in our regression analysis some analysts drop out due to missing observations on required independent variables, especially *LMAFE*. For this reason, while the average mean-adjusted value for each variable is zero (by definition), it is not necessarily the case that the average mean-adjusted values reported in Panel B of Table 1 are zero. When we re-estimate our Eq. 2 using mean-adjustment with respect only to observations that have all the required data, the coefficient on *CFF* is still significantly negative and our inferences are unchanged.

of analysts following the firm. We do this to examine whether the result in Panel C continues to hold across firms of varying economic significance. As reported in Panel D, the result that analysts who issue cash flow forecasts issue more accurate earning forecasts is consistent across all three analyst following groups.[17]

While the above univariate analyses yield results suggesting earnings forecast accuracy is higher when analysts also issue cash flow forecasts, such analyses do not control for other factors, such as forecast age, that can impact forecast accuracy. In the next section we discuss the results from the pooled regression analysis conducted at the analyst level, which employs control variables to ensure that any superior forecasting performance persists in the presence of other determinants of earnings forecast accuracy documented in the extant literature.

4.1.2.2 Pooled regression results Table 2 reports the results from the pooled regression (Eq. 2) of mean-adjusted earnings forecast accuracy (*MAFE*) on the indicator variable for the issuance of cash flow forecasts and control variables. The coefficient on the indicator variable for cash flow forecast issuance is significantly positive using *t*-statistics clustered by analyst ($CFF = 0.006$, $p\text{-value} = 0.05$). This result suggests that, relative to earnings forecasts issued in isolation, earnings forecasts accompanied by cash flow forecasts are on average 0.6% more accurate than the mean forecast of *all* analysts following the firm.[18] This result is consistent with analysts issuing more accurate earnings forecasts when they also issue cash flow forecasts.

The reported coefficients of the control variables are largely consistent with existing research findings. For example, we find significantly positive coefficients on *LMAFE* and *MFREQ*, indicating that higher prior period earnings forecast accuracy (*LMAFE*) and greater frequency of earnings forecasts (*MFREQ*) are associated with more accurate earnings forecasts. We also find that older forecasts (*MAGE*) are less accurate. The other control variables are not significant.[19] In

[17] We also partition the sample based on (i) total assets, (ii) total sales, and (iii) market value of equity. We obtain similar results across all sample partitions.

[18] Recall that for each analyst, *MAFE* is measured as the absolute earnings forecast error relative to the mean absolute forecast error of *all* analysts following the same firm in the same year (regardless of whether the analysts issue cash flow forecasts). Hence, this 0.6% improvement in forecast accuracy is not a simple comparison of the forecast errors of earnings forecasts issued with cash flow forecasts and those issued in isolation (unlike our univariate comparison of differential forecast accuracy in Panels C and D of Table 1). Rather, this analysis suggests that relative to earnings forecasts issued in isolation, earnings forecasts accompanied by cash flow forecasts are 0.6% more accurate than the mean earnings forecasts issued for the firm. Therefore, this coefficient provides a lower bound estimate of the difference in earnings forecast accuracy between earnings forecasts issued with cash flow forecasts and those issued in isolation. While the *MAFE* measure may mute the economic significance of our reported findings, we believe its role in controlling for firm-year specific factors affecting earnings forecasting difficulty is of vital importance to the validity of our analyst level tests reported in Tables 2 through 5.

[19] We examine whether multicollineraity among variables might influence our regression results reported in Table 2. Kennedy (1992) suggests that a Variance Inflation Factor (VIF) greater than 10 is indicative of problematic collinearity. The VIFs are less than two for all variables in the regressions reported in Table 2. The absolute correlations between *CFF* and all independent variables do not exceed 0.15 while the absolute correlations among the other independent variables are all lower than 0.6. Hence, multicollinearity is unlikely to affect our results.

Table 2 The association between the issuance of a cash flow forecast and earnings forecast accuracy regression based on pooled sample

Model: $MAFE_{ijt} = \alpha_{ijt} + \beta_1 CFF_{ijt} + \beta_2 LMAFE_{ijt} + \beta_3 MAGE_{ijt} + \beta_4 MFREQ_{ijt} + \beta_5 MFEXP_{ijt} + \beta_6 MGEXP_{ijt} + \beta_7 DTOP10_{it} + \beta_8 MNCOS_{ijt} + \beta_9 MNSIC2_{ijt} + YEAR + \varepsilon_{ijt}$ (2)

	Pred. sign	Coefficient	*p*-Value
Intercept	?	0.003	0.610
CFF	+	**0.006**	**0.050**
LMAFE	+	0.065	<.001
MAGE	−	−0.435	<.001
MFREQ	+	0.047	<.001
MFEXP	+	−0.004	0.984
MGEXP	+	−0.004	0.936
DTOP10	+	0.002	0.313
MNCOS	−	0.012	0.999
MNSIC2	−	0.018	0.997
Adj. R^2		16.9%	
N		$N_{\text{CFF}} = 171{,}944$; $N_{\text{NO-CFF}} = 208{,}736$	

p-Values are one-sided for variables with directional predictions. We report $(1 - p)$ values for coefficients that assume a sign opposite to the one predicted. We report analyst-clustered standard errors. All variables are winsorized at the 1% and 99% levels

Definition of variables:

CFF = a dummy variable set to 1 if analyst *i* issues a cash flow forecast for firm *j* in year *t*, and set to 0 otherwise; *MAFE* = mean-adjusted absolute earnings forecast error, calculated as the difference between the absolute earnings forecast error for analyst *i* for firm *j* in year *t* and the mean absolute earnings forecast error for firm *j* in year *t* scaled by the mean absolute earnings forecast error for firm *j* in year *t*. We multiply *MAFE* values by negative one, so larger values are consistent with more accurate earnings forecasts; *LMAFE* = lagged mean-adjusted absolute earnings forecast error, calculated as analyst *i*'s *MAFE* value for firm *j* in year $t - 1$; *MAGE* = age (in days) of analyst *i*'s earnings forecast for firm *j*'s earnings at time *t* minus the age of the average analyst's earnings forecast following firm *j* in year *t*, scaled by the age of the average analyst's earnings forecast following firm *j* in year *t*; *MFREQ* = number of forecasts issued by analyst *i* for firm *j*'s earnings in year *t* minus the average number of forecasts issued for firm *j* in year *t* scaled by the average number of forecasts issued for firm *j* in year *t*; *MFEXP* = number of years through year *t* for which analyst *i* supplied at least one earnings forecast for firm *j* minus the average number of years analysts following firm *j* had supplied earnings forecasts through year *t* scaled by the average number of years analysts following firm *j* had supplied earnings forecasts through year *t*; *MGEXP* = number of years through year *t* for which analyst *i* supplied at least one earnings forecast minus the average number of years through year *t* analysts supplied at least one earnings forecast scaled by the average number of years through year *t* analysts supplied at least one earnings forecast; *DTOP10* = a dummy variable set to 1 if analyst *i* is employed by a firm in the top size decile during year *t*, and set to 0 otherwise. Size deciles are calculated based on the number of analysts employed in year *t*; *MNCOS* = number of firms for which analyst *i* supplied at least one earnings forecast in year *t* minus the average number of firms followed by an analyst following firm *j* in year *t* scaled by the average number of firms followed by an analyst following firm *j* in year *t*; *MNSIC2* = number of two-digit SICs for which analyst *i* supplied at least one earnings forecast in year *t* minus the average number of two-digit SICs followed by an analyst following firm *j* at time *t* scaled by the average number of two-digit SICs followed by an analyst following firm *j* at time *t*

summary, the evidence presented in Table 2 is consistent with H1. Specifically, earnings forecast accuracy is higher when analysts issue both cash flow and earnings forecasts compared to when they only issue earnings forecasts.

While we directly address concerns over firm specific characteristics that affect forecast accuracy and analysts' decision to issue cash flow forecasts by (i) using a relative measure of forecast accuracy (*MAFE*) and (ii) including specific control variables in Eq. 2, concerns over adequate controls for analyst and analyst-firm specific characteristics (for example, ability and experience) may still remain. Therefore, we employ two alternative empirical specifications to corroborate the inferences that can be drawn from our pooled analysis in Eq. 2. We discuss these two alternative empirical specifications and the associated results in the following two sections.

4.2 Alternative empirical specification (1)—same-analyst-different-firms

4.2.1 Empirical model

We examine the accuracy of earnings forecasts made by an analyst who issues cash flow and earnings forecasts for some firms but issues only earnings forecasts for other firms. For any given analyst, we expect earnings forecasts that are accompanied by cash flow forecasts to be more accurate than earnings forecasts that this same analyst issues in isolation. This analysis holds constant unobservable analyst specific characteristics, such as ability, that are difficult to capture. Since this is a within-analyst research design, concerns over the effect of analyst specific characteristics that might affect forecast accuracy and the analysts' choice to issue cash flow forecast that are not captured in Eq. 2 are mitigated. We estimate the following regression separately for each analyst with at least 20 observations in our sample period:

$$\begin{aligned} MAFE_{jt} = {} & \alpha_{jt} + \beta_1 CFF_{jt} + \beta_2 LMAFE_{jt} + \beta_3 MAGE_{jt} + \beta_4 MFREQ_{jt} + \beta_5 MFEXP_{jt} \\ & + YEAR + \varepsilon_{jt} \end{aligned} \tag{3}$$

The variables are as defined in Eq. 2.[20] We include year dummies (*YEAR*) to control for time-varying changes to analyst specific characteristics such as ability, experience, and availability of resources. We also control for analyst-firm specific variables by including one period lagged mean-adjusted earnings forecast accuracy (*LMAFE*), mean-adjusted forecast age (*MAGE*), mean-adjusted forecast frequency (*MFREQ*) and mean-adjusted firm-specific forecasting experience (*MFEXP*). As we estimate Eq. 3 by analyst, we examine and report the mean coefficients of the analyst specific equations and the associated Fama-MacBeth *t*-statistics and expect to find a significantly positive coefficient on *CFF*.

4.2.2 Empirical results

Table 3 reports the mean coefficient estimates from 5,643 analyst-specific regressions and the Fama-MacBeth *t*-statistics based on our within-analyst research

[20] Note that we estimate this regression separately for each analyst, so even though the variables are still measured at the analyst-firm-year level, analyst subscripts are unnecessary in this model.

Table 3 The association between the issuance of a cash flow forecast and earnings forecast accuracy regression based on same analyst with different firms

Model: $MAFE_{jt} = \alpha_{jt} + \beta_1 CFF_{jt} + \beta_2 LMAFE_{jt} + \beta_3 MAGE_{jt} + \beta_4 MFREQ_{jt} + \beta_5 MFEXP_{jt} + YEAR + \varepsilon_{jt}$ (3)

	Pred. sign	Mean coefficient	p-Value
CFF	+	**0.050**	**<.001**
LMAFE	+	0.034	>.001
MAGE	–	–0.344	<.001
MFREQ	+	0.049	<.001
MFEXP	+	–0.009	0.991
Adj. R^2		20.8%	
N		5,643	

p-Values are one-sided for variables with directional predictions. We report $(1 - p)$ values for coefficients that assume a sign opposite to the one predicted. All variables are winsorized at the 1% and 99% levels

Equation 3 is estimated separately for each analyst, for a total of 5,643 unique regressions. We require a minimum of 20 observations for each regression. We report the mean of all 5,643 coefficients. p-Values are calculated based on the average coefficient across all 5,643 regressions. We also report the average Adj. R^2 across all 5,643 regressions

Definition of variables:

MAFE = mean-adjusted absolute earnings forecast error, calculated as the difference between the absolute earnings forecast error for analyst i for firm j in year t and the mean absolute earnings forecast error for firm j in year t scaled by the mean absolute earnings forecast error for firm j in year t. We multiply MAFE values by negative one, so larger values are consistent with more accurate earnings forecasts; *CFF* = a dummy variable set to 1 if analyst i issues a cash flow forecast for firm j in year t, and set to 0 otherwise; *LMAFE* = lagged mean-adjusted absolute earnings forecast error, calculated as analyst i's *MAFE* value for firm j in year $t-1$; *MAGE* = age (in days) of analyst i's earnings forecast for firm j's earnings at time t minus the age of the average analyst's earnings forecast following firm j in year t, scaled by the age of the average analyst's earnings forecast following firm j in year t; *MFREQ* = number of forecasts issued by analyst i for firm j's earnings in year t minus the average number of forecasts issued for firm j in year t scaled by the average number of forecasts issued for firm j in year t; *MFEXP* = number of years through year t for which analyst i supplied at least one earnings forecast for firm j minus the average number of years analysts following firm j had supplied earnings forecasts through year t scaled by the average number of years analysts following firm j had supplied earnings forecasts through year t; *YEAR* = year dummies

design. The mean coefficient on the indicator variable for cash flow forecast issuance (*CFF* = 0.050, p-value < 0.001) is significantly positive.[21] This result suggests that, relative to earnings forecasts issued in isolation, when analysts accompany their earnings forecasts with cash flow forecasts, their earnings forecasts are on average 5% more accurate than the mean forecast. This result is consistent

[21] The above test is conducted on a sample in which some firms do not have cash flow forecasts. This might raise the question of whether we adequately control for firm-characteristics that affect the issuance of cash flow forecasts. We test the robustness of the results by further restricting the above sample to only firm-years with at least one cash flow forecast, resulting in 5,174 unique analyst regressions. Our results are robust to this design choice. Specifically, the coefficient (p-value) on *CFF* is 0.051 (<0.001). The other coefficients are very similar to those reported in Table 3.

with the results of our pooled analysis and suggests that analysts issue more accurate earnings forecasts when they also issue cash flow forecasts for the firm.[22]

4.3 Alternative empirical specification (2)—initiation and cessation of cash flow forecasts

4.3.1 Empirical models

In addition to the above analyst specific analysis, we also use an interrupted time-series specification and examine changes in relative earnings forecast accuracy for the same analyst-firm pairing surrounding the issuance and cessation of cash flow forecast issuance. This within-analyst and within-firm specification further addresses the issue of inadequate controls for analyst and analyst-firm specific characteristics. We align our analyst-firm observations in event time and estimate the following regressions:

$$MAFE_{ijt} = \alpha_{ijt} + \beta_1 START_{ij} + \beta_2 LMAFE_{ijt} + \beta_3 MAGE_{ijt} + \beta_4 MFREQ_{ijt} + YEAR + \varepsilon_{ijt} \quad (4)$$

$$MAFE_{ijt} = \alpha_{ijt} + \beta_1 STOP_{ij} + \beta_2 LMAFE_{ijt} + \beta_3 MAGE_{ijt} + \beta_4 MFREQ_{ijt} + YEAR + \varepsilon_{ijt} \quad (5)$$

For each analyst-firm pair, we examine changes in the mean-adjusted analyst forecast errors in the year in which the analyst starts or stops issuing cash flow forecasts for a firm. Specifically, we set *START* equal to one in the first year in which analyst *i* issues a cash flow forecast for firm *j*, and equal to zero in the year immediately before analyst *i*'s first cash flow forecast for firm *j*. Similarly, we set *STOP* equal to one in the first year after analyst *i*'s last cash flow forecast for firm *j*, and equal to zero in the year of analyst *i*'s last cash flow forecast for firm *j*. In both sets of equations, we maintain controls for analyst-firm specific variables by including one period lagged mean-adjusted earnings forecast accuracy (*LMAFE*), mean-adjusted age of the earnings forecast (*MAGE*), and mean-adjusted earnings forecast frequency (*MFREQ*). We also include year dummies (*YEAR*) to control for cross-sectional dependence and calculate analyst-clustered standard errors to control for time-series dependence in earnings forecast accuracy (Petersen 2009). We expect a significantly positive coefficient on *START* and a significantly negative coefficient on *STOP*. That is, we expect earnings forecast accuracy to improve (worsen) after analysts start (stop) issuing cash flow forecasts for a firm.

[22] The results reported in Table 3 further distinguish this study from Ertimur et al. (2008), who hypothesize that analysts issue non-earnings (e.g., revenue) forecasts in order to signal their superior ability. If analysts issue cash flow forecasts to signal their innate forecasting ability, we would not expect to find that an individual analyst's earnings forecast accuracy varies across firms depending on whether a cash flow forecast is issued for the firm because, in this analyst specific analysis, the analysts' ability is held constant across all firms being covered. However, consistent with our hypothesis that analysts' earnings forecast accuracy improves when the analysts forecast the full set of financial statements and issue cash flow forecasts, the coefficient on CFF is significantly positive. This result is unlikely to be explained by Ertimur et al. (2008) signaling hypothesis.

4.3.2 Empirical results

Table 4 reports the results on the estimation of Eq. 4. The coefficient on *START* in Panel A of Table 4 is negative but insignificant. This result does not support our expectation and is inconsistent with the results reported in Tables 1 through 3.

To further explore whether this insignificant result may be attributable to other factors, we identify two patterns of cash flow forecast issuance—analysts who initiate and issue cash flow forecasts for the firm beyond the year of the initial cash flow forecast, and analysts who initiate and issue cash flow forecasts for only one year. As reported in Panel B of Table 4, we identify 7,722 analyst-firm observations in which the issuance of cash flow forecast starts in year t and then continues for at least one more year (i.e., in year $t + 1$ and beyond) ("persistent cash flow forecasters"). We also identify 9,373 analyst-firm observations in which the issuance of a cash flow forecast is initiated in year t and then stops in year $t + 1$ for a firm ("non-persistent cash flow forecasters").

In Panel B of Table 4, we report the results from estimating Eq. 4 separately for the persistent cash flow forecasters and non-persistent cash flow forecasters. We find that the earnings forecast accuracy of persistent cash flow forecasters improves significantly after the issuance of cash flow forecasts ($START = 0.023$, $p = 0.048$). This result suggests that relative to the year immediately before analysts start issuing cash flow forecasts, analysts' earnings forecast errors are on average 2.3% smaller than the mean forecast error in the year of the first cash flow forecast. However, we find relative earnings forecast accuracy worsens for non-persistent cash flow forecasters ($START = -0.019$, $p = 0.064$). Thus, the insignificantly negative coefficient on *START* in Panel A is the result of pooling these two groups of analyst-firm observations with differential forecasting patterns. Overall, we find evidence consistent with H1 only for analysts who issue cash flow forecasts for more than one year.[23]

In Table 5, we report results examining whether earnings forecast accuracy worsens when analysts stop issuing cash flow forecasts for a firm. As reported in Panel A of Table 5, the coefficient on *STOP* is significantly negative ($STOP = -0.046$, $p < 0.001$). This finding suggests that relative to the last year the analyst issues a cash flow forecast, analysts' earnings forecast errors are on average 4.6% larger than the mean forecast error in the year the analyst stops issuing cash flow forecasts. To be consistent with the analysis of persistent cash flow forecasters and non-persistent cash flow forecasters as reported in Table 4, we also separately examine the effects of stopping cash flow forecast issuance for these two patterns of forecasters. Specifically, we identify analyst-firm observations in which cash flow forecasts have been issued for more than one year before the year of cessation ("persistent cash flow forecasts") and analyst-firm observations in which cash flow forecasts have only been issued for one year ("non-persistent cash flow

[23] In an untabulated analysis, we find that in the year when cash flow forecasts are initiated, cash flow forecast accuracy is significantly higher for persistent versus non-persistent cash flow forecasters. While we do not examine the determinants of persistent and non-persistent cash flow forecasters, this result suggests that one of the potential reasons why analysts stop forecasting cash flows for some firms after only one year is lower cash flow forecast accuracy.

Table 4 The association between the issuance of a cash flow forecast and earnings forecast accuracy initiation of cash flow forecast issuance

$$MAFE_{ijt} = \alpha_{ijt} + \beta_1 START_{ij} + \beta_2 LMAFE + \beta_3 MAGE_{ijt} + \beta_4 MFREQ_{ijt} + YEAR + \varepsilon_{ijt} \quad (4)$$

	All analyst-firm observations		
	Pred. sign	Coefficient	p-Value
Panel A: All analyst-firm observations			
Intercept	?	0.029	0.083
START	+	**−0.007**	**0.239**
LMAFE	+	0.048	<.001
MAGE	−	−0.400	<.001
MFREQ	+	0.018	0.001
Adj. R^2		11.8%	
N		N_{PRE} = 17,095	
		N_{POST} = 17,095	

	Persistent cash flow forecasts[a,c]			Non-persistent cash flow forecasts[b,c]		
	Pred. sign	Coefficient	p-Value	Pred. sign	Coefficient	p-Value
Panel B: Persistent versus non-persistent cash flow forecasts—regression analysis						
Intercept	?	0.187	0.633	?	0.033	0.080
START	+	**0.023**	**0.048**	−	**−0.019**	**0.064**
LMAFE	+	0.049	<.001	+	0.046	<.001
MAGE	−	−0.360	<.001	−	−0.417	<.001
MFREQ	+	0.009	0.150	+	0.032	0.001
Adj. R^2		9.5%			13.1%	
N		N_{PRE} = 7,722			N_{PRE} = 9,373	
		N_{POST} = 7,722			N_{POST} = 9,373	

p-Values are one-sided for variables with directional predictions. We report $(1 - p)$ values for coefficients that assume a sign opposite to the one predicted. We report analyst-clustered standard errors. All variables are winsorized at the 1% and 99% levels

[a] We define "Persistent Cash Flow Forecasts" as analyst-firm observations in which cash flow forecast issuance is initiated for firm j in year t by analyst i, and the issuance of cash flow forecast continues for firm j in year $t + 1$ by analyst i

[b] We define "Non-persistent Cash Flow Forecasts" as analyst-firm observations in which cash flow forecast issuance is initiated for firm j in year t by analyst i and the issuance of cash flow forecast ceases for firm j in year $t + 1$ by analyst i

[c] p-Values are associated with t-statistics. When tests indicate inequality of variances at the 10% level, we report t-statistics that assume unequal variances. Otherwise, we report t-statistics that assume equal variances

Definition of variables:

MAFE = mean-adjusted absolute earnings forecast error, calculated as the difference between the absolute earnings forecast error for analyst i for firm j in year t and the mean absolute earnings forecast error for firm j in year t scaled by the mean absolute earnings forecast error for firm j in year t. We multiply *MAFE* values by negative one, so larger values are consistent with more accurate earnings forecasts; *START* = a dummy variable set to 1 if analyst i issues a cash flow forecast for firm j in year t for the first time, and set to 0 in year $t - 1$; *LMAFE* = lagged mean-adjusted absolute earnings forecast error, calculated as analyst i's *MAFE* value for firm j in year $t - 1$; *MAGE* = age (in days) of analyst i's forecast for firm j's earnings at time t minus the age of the average analyst's forecast following firm j in year t, scaled by the age of the average analyst's forecast following firm j in year t; *MFREQ* = number of forecasts issued by analyst i for firm j's earnings in year t minus the average number of forecasts issued for firm j in year t scaled by the average number of forecasts issued for firm j in year t; *YEAR* = year dummies

Table 5 The association between the issuance of a cash flow forecast and earnings forecast accuracy cessation of cash flow forecast issuance

$$MAFE_{ijt} = \alpha_{ijt} + \beta_1 STOP_{ij} + \beta_2 LMAFE + \beta_3 MAGE_{ijt} + \beta_4 MFREQ_{ijt} + YEAR + \varepsilon_{ijt} \quad (5)$$

	All analyst-firm observations		
	Pred. sign	Coefficient	*p*-Value
Panel A: All analyst-firm observations			
Intercept	?	0.027	0.067
STOP	−	**−0.046**	**<.001**
LMAFE	+	0.072	<.001
MAGE	−	−0.405	<.001
MFREQ	+	0.027	<.001
Adj. R^2		14.3%	
N		N_{PRE} = 17,256	
		N_{POST} = 17,256	

	Persistent cash flow forecasts[a,c]			Non-persistent cash flow forecasts[b,c]		
	Pred. sign	Coefficient	*p*-Value	Pred. sign	Coefficient	*p*-Value
Panel B: Persistent versus non-persistent cash flow forecasts—regression analysis						
Intercept	?	−0.003	0.875	?	0.092	<.001
STOP	−	**−0.041**	**0.001**	?	**−0.056**	**<.001**
LMAFE	+	0.074	<.001	+	0.067	<.001
MAGE	−	−0.406	<.001	−	−0.403	<.001
MFREQ	+	0.020	0.022	+	0.035	0.001
Adj. R^2		14.0%			14.8%	
N		N_{PRE} = 10,646			N_{PRE} = 6,610	
		N_{POST} = 10,646			N_{POST} = 6,610	

p-Values are one-sided for variables with directional predictions. We report $(1 - p)$ values for coefficients that assume a sign opposite to the one predicted. We report analyst-clustered standard errors. All variables are winsorized at the 1% and 99% levels

[a] We define "Persistent Cash Flow Forecasts" as analyst-firm observations in which cash flow forecasts have been issued for more than one year (i.e., in year $t-1$ and before) by analyst *i* for firm *j* before cessation of cash flow forecast in year *t*

[b] We define "Non-persistent Cash Flow Forecasts" as analyst-firm observations in which cash flow forecasts have been issued for only one year (i.e., in year $t-1$) by analyst *i* for firm *j* before cessation of cash flow forecast in year *t*

[c] *p*-Values are associated with *t*-statistics. When tests indicate inequality of variances at the 10% level, we report *t*-statistics that assume unequal variances. Otherwise, we report *t*-statistics that assume equal variances

Definition of variables:

MAFE = mean-adjusted absolute earnings forecast error, calculated as the difference between the absolute earnings forecast error for analyst *i* for firm *j* in year *t* and the mean absolute earnings forecast error for firm *j* in year *t* scaled by the mean absolute earnings forecast error for firm *j* in year *t*. We multiply *MAFE* values by negative one, so larger values are consistent with more accurate earnings forecasts; *STOP* = a dummy variable set to 1 if analyst *i* does not issue a cash flow forecast for firm *j* in year *t* after having issued a cash flow forecast for firm *j* in year $t-1$, and set to 0 in year $t-1$; *LMAFE* = lagged mean-adjusted absolute earnings forecast error, calculated as analyst *i*'s *MAFE* value for firm *j* in year $t-1$; *MAGE* = age (in days) of analyst *i*'s forecast for firm *j*'s earnings at time *t* minus the age of the average analyst's forecast following firm *j* in year *t*, scaled by the age of the average analyst's forecast following firm *j* in year *t*; *MFREQ* = number of forecasts issued by analyst *i* for firm *j*'s earnings in year *t* minus the average number of forecasts issued for firm *j* in year *t* scaled by the average number of forecasts issued for firm *j* in year *t*; *YEAR* = year dummies forecasts"). As reported in Panel B of Table 5, our sample consists of 10,646 persistent cash flow forecasters and 6,610 non-persistent cash flow forecasters. Panel B of Table 5 offers results consistent with those presented in Panel A. These results suggest earnings forecast accuracy worsens for both persistent and non-persistent cash flow forecasters when the analyst stops issuing cash flows forecasts.

4.4 Summary on testing H1

In summary, based on the pooled analysis, we find that when analysts issue both cash flow and earnings forecasts simultaneously, their earnings forecasts are more accurate than when they only issue earnings forecasts. Based on the same-analyst-different-firms specification, we also find that a given analyst's earnings forecasts are more accurate when the analyst simultaneously issues both cash flow and earnings forecast relative to when the analyst only issues earnings forecasts. In addition, we find improvements in earnings forecast accuracy when analysts start to issue cash flow forecasts and continue to do so for more than a year. We also find worsening in earnings forecast accuracy when analysts cease to issue cash flow forecasts. Overall, these results provide evidence in support of H1, indicating earnings forecast accuracy is improved when analysts issue cash flow forecasts in addition to earnings forecasts.[24]

5 Do analysts better understand the persistence of earnings components when they issue cash flow forecasts?

5.1 Empirical models

When we examine the hypothesis that earnings forecasts are more accurate when analysts issue cash flow forecasts, we assume that analysts gain a better understanding of the components of earnings when they issue both cash flow and earnings forecasts compared to when they issue only earnings forecasts. We directly examine this assumption by investigating whether analysts better understand the persistence of the cash flow and accrual components of earnings when they issue cash flow forecasts. We estimate the following set of regressions to test H2:[25]

[24] Since we find earnings forecast accuracy to be positively associated with the issuance of cash flow forecasts, and because cash flow is a component of earnings, we expect to observe empirically that cash flow forecast *accuracy* is positively associated with earnings forecast accuracy. We focus on a restricted sample consisting of only earnings forecasts issued with cash flow forecasts and replace the indicator variable for cash flow forecast issuance (*CFF*) in Eq. 2 with a measure of mean-adjusted cash flow forecast accuracy. In untabulated analysis, we find a positive coefficient on mean-adjusted cash flow forecast accuracy indicating that cash flow forecast accuracy is indeed positively associated with earnings forecast accuracy. This relation continues to hold even after we replace the contemporaneous cash flow forecast accuracy measure with lagged mean-adjusted cash flow forecast accuracy in an effort to mitigate any mechanical relation between current period cash flow and earnings forecast accuracy.

[25] Equation 6 is estimated at the firm-year level while Eqs. 7–9 are estimated at the analyst-firm-year level. When we estimate Eq. 6 at the analyst-firm-year level, we obtain very similar results.

$$EPS_{jt} = \delta_0 + \delta_1 ACC_{jt-1} + \delta_2 CFO_{jt-1} + \varepsilon_{jt} \tag{6}$$

$$FEPS_{ijt} = \lambda_0 + \lambda_1 ACC_{jt-1} + \lambda_2 CFO_{jt-1} + \mu_{jt} \tag{7}$$

$$FERR_{ijt} = \gamma_0 + \gamma_1 ACC_{jt-1} + \gamma_2 CFO_{jt-1} + v_{it} \tag{8}$$

$$\begin{aligned} FERR_{ijt} = {} & \omega_0 + \omega_1 ACC_{jt-1} + \omega_2 ACC_{jt-1} \times CFF_{jt} + \omega_3 CFO_{jt-1} \\ & + \omega_4 CFO_{jt-1} \times CFF_{jt} + \xi_{jt} \end{aligned} \tag{9}$$

EPS, *ACC* and *CFO* are earnings per share, total accruals per share and operating cash flow per share, respectively, all scaled by beginning-of-period stock price. *FEPS* is the forecasted earnings per share scaled by beginning-of-period stock price. *FERR* is the forecast error calculated as the difference between scaled earnings per share (*EPS*) and scaled forecasted earnings per share (*FEPS*).[26] *CFF* is an indicator variable equal to one if analyst i issues cash flow forecasts simultaneously with earnings forecasts for firm j in year t, and set equal to zero if analyst i only issues earnings forecasts for firm j in year t. We estimate Eqs. 6 through 9 annually and examine the mean coefficients of the estimated equations and report Fama-MacBeth t-statistics.

In Eq. 6, δ_1 and δ_2 represent respectively the persistence of the accrual and cash flow components of earnings as implied by the earnings time-series. Correspondingly in Eq. 7, λ_1 and λ_2 represent, respectively the persistence weights that analysts assign to the accrual and cash flow components of earnings as implied by their forecasts of earnings. Consistent with Ahmed et al. (2006) and Yu (2007), we expect to find that analysts underweight the persistence of both the accrual and cash flow component of earnings. That is, in Eq. 8, we expect the coefficient on *ACC* (γ_1) to be significantly positive because γ_1 represents the difference in accrual persistence between that implied by the earnings time-series and that implied by analysts' earnings forecasts. Similarly, we expect the coefficient on *CFO* (γ_2) to be significantly positive because λ_2 represents the difference between cash flow persistence implied by the earnings time-series and that implied by analysts' earnings forecasts. If analysts better understand the implications of current period accruals for future period earnings when they issue both cash flow and earnings forecasts, we expect the coefficient on $ACC \times CFF$ (ω_2) in Eq. 9 to be significantly negative. That is, analysts who issue both earnings and cash flow forecasts underestimate the persistence of accruals *less* than do analysts who only issue earnings forecasts. Similarly, if analysts better understand the implications of current period cash flows for future period earnings when they issue both cash flow and earnings forecasts, we expect the coefficient on$ACC \times CFF$ (ω_4) in Eq. 9 to be

[26] For Eqs. 6–9, Compustat data item 18, earnings before extraordinary items and discontinued operations, is used to measure actual earnings rather than actual earnings from *I/B/E/S*. We do this to be consistent with the use of Compustat data items to obtain accruals (*ACC*) and cash flows (*CFO*), which are not widely available on *I/B/E/S*. Compustat data item 18 is consistent with the description from *I/B/E/S* that analysts typically forecast earnings after discontinued operations, extraordinary charges, and other non-operating items. As a comparison, the mean (median) of Compustat data item 18 is 0.32 (0.47) while that for the *I/B/E/S* actual earnings is 0.30 (0.32). Furthermore, the correlation between Compustat data item 18 and *I/B/E/S* actual earnings is 0.72. We offer further robustness checks on this design choice and detail our investigation in Sect. 7.2.

significantly negative. That is, analysts who issue both earnings and cash flow forecasts underestimate the persistence of cash flows *less* than do analysts who only issue earnings forecasts.[27]

5.2 Empirical results

Table 6 reports the results from our analysis of the differences in accrual and cash flow persistence between that implied by the earnings time-series and that reflected in analysts' earnings forecasts. We report the regression results from estimating Eqs. 6–9 in columns (1) through (4), respectively. Consistent with prior research (Sloan 1996), in column (1) we find cash flows ($CFO = 0.522$) are more persistent than accruals ($ACC = 0.446$).[28]

In column (2), we regress analysts' earnings forecasts for next period earnings on current period accruals and cash flows. We find that analysts recognize the differential persistence of current cash flows and accrual components of earnings for future earnings. The coefficient on accrual ($ACC = 0.253$) is smaller than that on cash flows ($CFO = 0.309$). However both coefficients are smaller than those from the earnings persistence model in column (1). This suggests that analysts underweight the persistence of both accruals and cash flows. In column (3), we formally examine whether this underweighting is statistically significant by regressing analysts' forecast errors (actual EPS minus analysts' forecasted EPS) on accruals and cash flows. The coefficients on *ACC* (0.223) and *CFO* (0.237) are both significantly positive. This indicates that, consistent with findings in prior research (Ahmed et al. 2006; Yu 2007), analysts underweight the persistence of both accruals and cash flows.

The results in column (4) are the focus of our investigation. In column (4), we introduce the indicator variable for analyst cash flow forecast issuance (*CFF*) and interact this indicator variable with both the accrual and cash flow components of earnings. If analysts better understand the properties of the earnings components when they issue both cash flow and earnings forecasts, we expect analysts' underweighting of the persistence of the earnings components to be less severe with the issuance of cash flow forecasts. The coefficients on $ACC \times CFF$ (−0.078, p-value $= 0.004$) and $CFO \times CFF$ (−0.072, p-value $= 0.011$) are both significantly negative, and suggest that the underweighting of cash flows and accruals is mitigated by approximately 30% when analysts issue both cash flow and earnings forecasts. Thus, the results reported in Table 6 are consistent with H2, indicating that analysts better understand the persistence of the cash flow and accrual components of earnings when they issue both cash flow and earnings forecasts. Furthermore, this result suggests the finding that analysts issue more accurate earnings forecasts when they issue cash flow forecasts (H1) is driven by analysts'

[27] In Eq. 9, our focus is on whether analysts' underreaction to both cash flows and accruals is mitigated when they issue cash flow forecasts compared to when they do not issue cash flows forecasts. We do not predict or examine whether the underreaction to accruals is mitigated to a greater or lesser extent than is the underreaction to cash flows.

[28] In untabulated analysis, we find the difference in the persistence of cash flows (*CFF*) and accruals (*ACC*) is significant at the 1% level.

Table 6 Analysts' understanding of the implications of current accruals and cash flows for future earnings

Models: $EPS_{j,t} = \delta_0 + \delta_0 ACC_{j,t-1} + \delta_1 CFO_{j,t-1} + \varepsilon_{j,t}$ (6)

$FEPS_{i,j,t} = \lambda_0 + \lambda_1 ACC_{j,t-1} + \lambda_2 CFO_{j,t-1} + \mu_{j,t}$ (7)

$FERR_{i,j,t} = \gamma_0 + \gamma_1 ACC_{j,t-1} + \gamma_2 CFO_{j,t-1} + v_{i,t}$ (8)

$FERR_{i,j,t} = \omega_0 + \omega_1 ACC_{j,t-1} + \omega_2 ACC_{j,t-1} \times CFF_{j,t} + \omega_3 CFO_{j,t-1} + \omega_4 CFO_{j,t-1} \times CFF_{j,t} + \xi_{j,t}$ (9)

Dependent variable	Column (1) Model 6 Earnings$_{it}$	Column (2) Model 7 Forecast$_{ijt}$	Column (3) Model 8 Forecast Error$_{ijt}$	Column (4) Model 9 Forecast Error$_{ijt}$
Intercept	0.002	0.015	−0.011	−0.011
	0.703	<.001	<.001	<.001
ACC_{jt-1}	0.446	0.253	0.223	0.247
	<.001	<.001	<.001	<.001
$ACC_{jt-1} * CFF_{jt}$				**−0.078**
				0.004
CFO_{jt-1}	0.522	0.309	0.237	0.261
	<.001	<.001	<.001	<.001
$CFO_{jt-1} * CFF_{jt}$				**−0.072**
				0.011
Adj. R^2	22.6%	24.3%	10.4%	11.2%
N	13	13	13	13

We estimate the above regressions each year ($N = 13$ years for all models) and calculate the mean coefficients and associated Fama-MacBeth t-statistics. p-Values are one-sided for variables with directional predictions. We report $(1 - p)$ values for coefficients that assume a sign opposite to the one predicted. All variables are winsorized at the 1% and 99% levels

Definition of variables:

EPS_{jt} = earnings before extraordinary items per share for firm j in year t, deflated by firm j's stock price at the end of year $t - 1$; $FEPS_{ijt}$ = analyst i's forecast of firm j's year t earnings per share, deflated by firm j's stock price at the end of year $t - 1$; $FERR_{ijt}$ = the difference between firm j's earnings per share in year t and analyst i's forecast of firm j's earnings in year t, deflated by firm j's stock price at the end of year $t - 1$; ACC_{jt-1} = total accruals for firm j in year $t - 1$, where accruals are calculated as the difference between earnings and operating cash flows; CFO_{jt-1} = operating cash flows per share for firm j in year $t - 1$; CFF_{jt} = a dummy variable set to 1 if analyst i issues a cash flow forecast for firm j in year t, and set to 0 otherwise

superior understanding of the time-series properties of earnings when they forecast both earnings and cash flows, consistent with the theoretical arguments made by Hirshleifer and Teoh (2003).[29]

[29] Raedy et al. (2006) propose a rational economic explanation for analysts' underreaction to earnings information. They argue that analysts have an asymmetric loss function. Specifically, that analysts' reputation suffers more (less) when subsequent information causes a revision in investor expectations in the opposite (same) direction as the analyst's prior earnings forecast revisions. By underreacting, analysts can avoid a revision in an opposite direction and avoid the associated greater reputation damage. Raedy et al. (2006) also predict a positive relation between analysts' underreaction to earnings information and the uncertainty regarding future earnings information. This suggests the underweighting of accrual and cash flow persistence decreases with the accuracy (as well the presence) of cash flow forecasts. To examine this proposition, we isolate only the analysts who issued a cash flow forecast, and we replace the indicator variable for cash flow forecast issuance (CFF) in Eq. 9 with a measure of cash flow forecast

6 Does cash flows forecast accuracy affect analysts' career outcomes?

6.1 Empirical model

Prior research documents that cash flow forecast issuance affects investor pricing of cash flows in the stock markets (DeFond and Hung 2003; Call 2008). Furthermore, brokerages based their firing decisions, in part, on earnings forecast accuracy of analysts (Mikhail et al. 1999; Hong and Kubik 2003). We examine whether brokerages also use cash flow forecast accuracy in their firing decisions. We estimate the following logistic model

$$Prob(FIRED_{it+1}) = \beta_0 + \beta_1 RAFE\_CF_{it} + \beta_2 RAFE_{it} + \beta_3 GEXP_{it} + \beta_4 BIAS_{it} + \beta_5 BOLD_{it} + YEAR + BROKER + \varepsilon_{it+1} \quad (10)$$

where, $FIRED_{it}$ = an indicator variable equal to 1 if the analyst permanently leaves the *I/B/E/S* database in year $t + 1$ or if the analyst changes to or adds a smaller brokerage affiliation in year $t + 1$, and 0 otherwise; $RAFE\_CF_{it}$ = the rank of the absolute cash flow forecast errors for analyst i averaged across all firms covered by analyst i in year t. Ranks are calculated relative to all other analysts issuing cash flow forecasts for the same firm in year t. Specifically, $RAFE\_CF$ is equal to $(1 - (\text{Rank}(CFFE_{ijt}) - 1)/((N_{jt}) - 1))$, where $CFFE_{ijt}$ is analyst i's absolute cash flow forecast error for firm j in year t, and N_{ijt} is the number of analysts issuing cash flow forecasts for firm j in year t. Larger (smaller) values of $RAFE\_CF$ are consistent with the analyst issuing cash flow forecasts that are more (less) accurate than other analysts, on average; $RAFE_{it}$ = the rank of the absolute earnings forecast errors for analyst i averaged across all firms covered by analyst i in year t. Ranks are calculated relative to all other analysts issuing earnings forecasts for the same firm in year t. Specifically, $RAFE$ is equal to $(1 - (\text{Rank}(EFE_{ijt}) - 1)/((N_{jt}) - 1))$, where EFE_{ijt} is analyst i's absolute earnings forecast error for firm j in year t, and N_{ijt} is the number of analysts issuing earnings forecasts for firm j in year t. Larger (smaller) values of $RAFE$ are consistent with the analyst issuing earnings forecasts that are more (less) accurate than other analysts; $GEXP_{it}$ = the number of years through year t for which analyst i has supplied at least one earnings forecast; $BIAS_{it}$ = the average earnings forecast bias of analyst i's earnings forecasts in year t. For each firm analyst i follows in year t, we set a dummy variable equal to 1 if analyst i's first forecast of firm j's year t earnings is greater than firm j's actual earnings in year t and analyst i's last forecast of firm j's year t earnings is less than firm j's actual earnings in year t, and 0 otherwise. For each analyst in each year, we use the average of this dummy variable across all firms the analyst follows; $BOLD_{it}$ = the average boldness of analyst i's earnings forecasts is year t. For each firm analyst i follows in year t, we measure the absolute deviation of analyst i's first

Footnote 29 continued
accuracy. Consistent with the prediction of a positive relation between underreaction and information uncertainty, we find (in an untabulated analysis) the underweighting of cash flows and accrual is mitigated to a greater extent when analysts issue more accurate cash flow forecasts.

forecast of firm *j*'s year *t* earnings from the average of all other analysts' first forecast of firm *j*'s year *t* earnings. For each analyst in each year, we use the average of this measure across all firms the analyst follows; *YEAR* = year dummies; *BROKER* = broker dummies.

Specifically, the measurement of *FIRED* is consistent with Ke and Yu (2006) and captures analysts who move from large to small brokerages or who leave the profession entirely. The definition of *FIRED* thus excludes observations of analysts who move to another brokerage of a similar or bigger size. Following Hong and Kubik (2003), a brokerage is considered large if it employs at least 25 analysts. We use the rank of analyst *i*'s absolute forecast errors relative to all other analysts to measure cash flow forecast accuracy (*RAFE_CF*) and earnings forecast accuracy (*RAFE*) to be consistent with Mikhail et al. (1999) and Hong et al. (2000), who show that it is relative forecast accuracy rather than absolute forecast accuracy that determines brokerages' firing decisions. We include the analysts' general experience (*GEXP*), year dummies (*YEAR*), and brokerage dummies (*BROKER*) as control variables. We also include the average bias of the analyst's earnings forecasts (*BIAS*) as Ke and Yu (2006) find that analysts who "walk down" their earnings forecasts are less likely to be fired. In addition, we include the boldness of analysts' earnings forecasts (*BOLD*) as Hong et al. (2000) find bold but inexperienced analysts are more likely to leave the profession. Our focus is on the coefficient on *RAFE_CF*. If brokerages use cash flows forecast accuracy in addition to earnings forecast accuracy to assess the performance of analysts, we expect a negative coefficient on *RAFE_CF*.

6.2 Empirical results

Since our focus is on the incremental effect of cash flow forecast accuracy on analyst career outcomes, beyond the effect of earnings forecast accuracy, we only present a hypothesis on the association between cash flow forecast accuracy and brokerages' firing decisions. However, for ease of comparison with existing research, we also present results examining the association between the *issuance* of cash flow forecasts and analysts' career outcomes.

Table 7 presents the results of our analyses on the effect of cash flow forecast issuance and cash flow forecast accuracy on analysts' career outcomes. Recall that, consistent with existing research (Mikhail et al. 1999; Ke and Yu 2006), we code the career outcome variable *FIRED* as 1 if an analyst permanently leaves the *I/B/E/S* database in year $t + 1$ or if the analyst moves to or adds a smaller brokerage affiliation in year $t + 1$.[30] Column (1) reports the logistic regression result on the association between cash flow forecast issuance and the probability of being fired. The results show that, after controlling for earnings forecast accuracy and other

[30] We find approximately 15% of analysts on the I/B/E/S database are affiliated with at least two brokerage houses in any given year. The reason of this multiple affiliation is unclear. Mikhail et al. (1999) report the same phenomenon using Zack's Investment Research database (see page 187 of their paper). Therefore, in our empirical analysis of career outcomes, we only include analysts with only one affiliation in year *t*. While this leads to a smaller sample size, the resulting definition of analysts being fired is clearer and more objective.

Table 7 The impact of cash flow forecasts on analyst career outcomes

Model: $Prob(FIRED_{it+1}) = \beta_0 + \beta_1 RAFE\_CF_{it} + \beta_2 RAFE_{it} + \beta_3 GEXP_{it} + \beta_4 BIAS_{it} + \beta_5 BOLD_{it} + YEAR + BROKER + \varepsilon_{it+1}$ (10)

	Pred. sign	Column (1) (*CFF*)			Column (2) (*RAFE_CF*)		
		Coefficient	*p*-Value	Marginal Δ in Prob.	Coefficient	*p*-Value	Marginal Δ in Prob.
Intercept	?	2.652	0.841	n/a	2.138	0.085	n/a
CFF	−	−0.535	<.001	−0.041			
RAFE_CF	−				−0.391	<.001	−0.020
RAFE	−	−2.714	<.001	−0.141	−2.802	<.001	−0.118
GEXP	−	0.030	0.999	0.014	0.023	0.999	0.012
BIAS	−	−2.454	<.001	−0.079	−2.329	<.001	−0.070
BOLD	−	0.000	0.682	0.000	−0.001	0.036	−0.000
Pseudo-R^2		15.9%			16.2%		
N		$N_{TURNOVER} = 41{,}084$			$N_{TURNOVER} = 11{,}969$		
		$N_{NO\text{-}TURNOVER} = 92{,}881$			$N_{NO\text{-}TURNOVER} = 34{,}456$		

p-Values are one-sided for variables with directional predictions. We report $(1 - p)$ values for coefficients that assume a sign opposite to the one predicted. Year dummies and broker dummies are suppressed. There are 15 (866) unique years (brokers) included in Eq. 10. The marginal change in probability is calculated as the change in the likelihood of the analyst experiencing turnover in year $t + 1$ when the underlying variable changes from the first to the third quartile of the sample distribution, holding all other independent variables at their respective means. All variables are winsorized at the 1% and 99% levels

Definition of variables:

FIRED = an indicator variable equal to 1 if the analyst permanently leaves the I/B/E/S database in year $t + 1$ or if the analyst changes to or adds a smaller brokerage affiliation in year $t + 1$, and 0 otherwise. A brokerage house is defined as large (small) if it employs at least 25 (fewer than 25) analysts in any given year (Hong and Kubik 2003); *CFF* = dummy variable set to 1 if analyst *i* issues a cash flow forecast for at least one firm in year *t*, and set to 0 otherwise; *RAFE* = the rank of the absolute earnings forecast errors for analyst *i* averaged across all firms *j* covered by analyst *i* in year *t*. Ranks are calculated relative to all other analysts issuing earnings forecast errors for firm *j* in year *t*. Specifically, *RAFE* is equal to $(1 - (\mathrm{Rank}(EFE_{ijt}) - 1)/((N_{jt}) - 1))$, where EFE_{ijt} is analyst *i*'s absolute earnings forecast error for firm *j* in year *t*, and N_{ijt} is the number of analysts issuing earnings forecasts for firm *j* in year *t*. Larger (smaller) values of *RAFE* are consistent with the analyst issuing earnings forecasts that are more (less) accurate than other analysts; *RAFE_CF* = the rank of the absolute cash flow forecast errors for analyst *i* averaged across all firms *j* covered by analyst *i* in year *t*. Ranks are calculated relative to all other analysts issuing cash flow forecast errors for firm *j* in year *t*. Specifically, *RAFE_CF* is equal to $(1 - (\mathrm{Rank}(CFFE_{ijt}) - 1)/((N_{jt}) - 1))$, where $CFFE_{ijt}$ is analyst *i*'s absolute cash flow forecast error for firm *j* in year *t*, and N_{ijt} is the number of analysts issuing cash flow forecasts for firm *j* in year *t*. Larger (smaller) values of *RAFE_CF* are consistent with the analyst issuing cash flow forecasts that are more (less) accurate than other analysts; *GEXP* = the number of years through year *t* for which analyst *i* supplied at least one earnings forecast; *BIAS* = the average earnings forecast bias of analyst *i*'s earnings forecasts in year *t*. For each firm analyst *i* follows in year *t*, we set a dummy variable equal to 1 if analyst *i*'s first forecast of firm *j*'s year *t* earnings is greater than firm *j*'s actual earnings in year *t* and analyst *i*'s last forecast of firm *j*'s year *t* earnings is less than firm *j*'s actual earnings in year *t*, and 0 otherwise. For each analyst in each year, our measure of bias (BIAS) is the average of this dummy variable across all firms the analyst follows; *BOLD* = the average boldness of analyst *i*'s earnings forecasts is year *t*. For each firm analyst *i* follows in year *t*, we measure the absolute deviation of analyst *i*'s first forecast of firm *j*'s year *t* earnings and the average of all other analysts' first forecast of firm *j*'s year *t* earnings. For each analyst in each year, *BOLD* is the average of this measure across all firms the analyst follows; *YEAR* = year dummies; *BROKER* = brokerage dummies determinants of analyst turnover, analysts who issue cash flow forecasts are less likely to be fired. In column (2), we test whether cash flow forecast accuracy is associated with brokerages' firing decisions (H3). The coefficient on ranked relative cash flow forecast accuracy is significantly negative ($RAFE\_CF = -0.391$, p-value < 0.001), suggesting that analysts with worse cash flows forecast accuracy are more likely to be fired. This result holds even after controlling for analysts' earnings forecast accuracy, which also has a significantly negative coefficient ($RAFE = -2.802$, p-value < 0.001). Since the unconditional probability of being fired is 25.78% in our sample of analysts issuing both cash flow and earnings forecasts (11,969–46,425), a move from the first to the third quartile of cash flow forecast accuracy increases the probability of being fired by 7.76% (2.0–25.78%). The coefficient on analysts' general experience (*GEXP*) is not significant while the coefficients on earnings forecasts bias (*BIAS*) and boldness (*BOLD*) are significant in the predicted direction.

Overall, the results in Table 7 suggest that when analysts issue both cash flow and earnings forecasts, brokerages base their firing decisions on both cash flow and earnings forecast accuracy. These results are consistent with those reported in a concurrent paper by Pandit et al. (2007). These authors identify analysts who leave the *I/B/E/S* database and find this measure of turnover is negatively associated with relative cash flow forecast accuracy after controlling for earnings forecast accuracy.

7 Sensitivity analyses

7.1 Access to management-provided information as an alternative explanation for H1

In our primary tests we employ a variety of controls for both analyst specific and analyst-firm specific factors that can affect earnings forecast accuracy, including the mean-adjustment of the dependent variable, sample selection, the use of various research designs, and the direct inclusion of control variables. Despite these controls, an alternative explanation for our results is that analysts who issue cash flow forecasts have access to management-provided information that can impact their earnings forecast accuracy (Chen and Matsumoto 2006). In such a scenario, analysts who issue both cash flow and earnings forecasts issue more accurate earnings forecasts simply because they have access to privileged information. To test this competing explanation, we re-run all our analyses (Tables 2, 3, 4, 5, 6 and 7) focusing only on the sample of analysts who issued cash flow forecasts after Regulation FD (2001 and beyond). Regulation FD prohibits selective disclosure of material information to specific groups of capital market participants. Thus, to the extent Regulation FD effectively rules out private communication between managers and analysts (for example, managers 'reviewing' analysts' forecasts), all analysts have equal access to management. Our results are unchanged in this alternative analysis, suggesting that it is the issuance of cash flow forecasts rather than access to management-provided information that leads to the increase in earnings forecast accuracy for analysts who issue cash flow forecasts.

7.2 Using Compustat data items in testing H2

As discussed in Sect. 5.1 and Footnote 26, to be consistent with the use of Compustat data items to obtain accruals (*ACC*) and cash flows (*CFO*), we use actual earnings from Compustat rather than from *I/B/E/S* when we test analysts' ability to understand the implications of current accruals and cash flows for future earnings. As a sensitivity check on this database choice, we form deciles based on the difference between Compustat actual earnings and *I/B/E/S* actual earnings and estimate Eq. 9 separately for each of the deciles. In untabulated results, we find that when analysts accompany their earnings forecasts with cash flow forecasts, their earnings forecasts exhibit less underweighting of the persistence of the earnings components in 8 of the 10 deciles. The consistency of this result across these deciles suggests that our inference is robust to any mismatch between Compustat and *I/B/E/S* actual earnings.

7.3 Using un-split-adjusted forecasts

We present our results using split-adjusted forecasts from *I/B/E/S*. We replicate all our analyses using the un-split-adjusted forecasts and the results remain the same. Split adjustment is more critical when using the *I/B/E/S* summary file where analyst forecasts are rounded to two decimal points, than when using the *I/B/E/S* detail file where analyst forecasts are rounded to four decimal places. We use the detail file for our primary analyses.

8 Summary and conclusions

We investigate whether analysts' earnings forecasts are more accurate when they issue both cash flow and earnings forecasts relative to when they only issue earnings forecasts. We also examine the effect of analysts' cash flow forecast accuracy on their career outcomes, incremental to the impact of earnings forecast accuracy.

We conjecture that when analysts forecast cash flows, they adopt a more structured approach to forecasting, which includes forecasting a full set of financial statements—the income statement, the balance sheet and the cash flows statement. This structured approach to forecasting imposes greater discipline on the earnings forecast, as articulation of the three financial statements is required (Lundholm and Sloan 2007). In addition, when analysts forecast a full set of financial statements, they are more likely to achieve a better understanding of the individual earnings components (for example, cash flows from operations and changes in working capital). We predict and find that earnings forecasts are more accurate when analysts issue both cash flow and earnings forecasts compared to when they only issue earnings forecasts. This result holds using various empirical specifications: (i) univariate analyses, (ii) a pooled regression in which we directly control for factors that affect both earnings forecast accuracy and the decision to issue cash flow forecasts, (iii) analyst specific regressions (to further control for unobservable analyst characteristics, such as ability) examining earnings forecast accuracy for analysts who issue cash flow forecasts for some firms but not for others, and (iv) changes regressions focusing on improvements (deterioration) in earnings forecast accuracy when analysts start (stop) issuing cash flow forecasts.

We also investigate the underlying assumption that when analysts issue both cash flow and earnings forecasts, they better understand the time-series properties of earnings components. Toward this end, we examine whether analysts have a better understanding of the persistence of accruals and cash flows when they issue cash flow forecasts. We find that analysts' earnings forecasts exhibit less underweighting of the persistence of accruals and cash flows when they issue cash flow forecasts for the firm, relative to when earnings forecasts are issued in isolation.

In addition, we find that cash flow forecast accuracy is associated with analysts' career outcomes. Specifically, we find that both earnings forecast accuracy *and* cash flow forecast accuracy are negatively associated with analyst turnover. This suggests that brokerages rely on both pieces of information (earnings forecast accuracy and cash flow forecast accuracy) when evaluating analysts.

Our study should be of interest to investors, academics, and to analysts themselves. Our study suggests that investors and academics can use a relatively inexpensive heuristic, whether earnings forecast is issued together with a cash flow forecast, to identify accurate forecasts of firms' future earnings. Our results are also relevant to analysts, as we document that their earnings forecast accuracy improves when they forecast both cash flows and earnings, and deteriorates when they revert back to only forecasting earnings. We further document that analysts' cash flow forecast accuracy is used by brokerages in making their firing decisions.

Acknowledgements We thank Russ Lundholm (Editor) and Phil Shane (Referee) for valuable insights. We have also benefitted from the discussion of Reuven Lehavy at the 2008 RAST Conference. We appreciate the helpful comments of Michael Clement, Pieter Elgers, Max Hewitt, Qianyun Huang, Ping-Sheng Koh, Bernadine Low, Ray Pfeiffer, Dave Piercey, Steve Rock, Richard Sloan, Siew Hong Teoh and workshop participants at the University of Colorado at Boulder, the University of Massachusetts Amherst, and participants at the 2008 AAA Annual meeting and 2008 RAST Conference. We also thank Julia Yu for research assistance.

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