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The effect of cash flow forecasts on accrual quality and benchmark beating ☆

John McInnis [a], Daniel W. Collins [b,*]

[a] McCombs School of Business, The University of Texas at Austin, Austin, TX, USA
[b] Henry B. Tippie Research Chair in Accounting, Tippie College of Business, The University of Iowa, Iowa City, IA, USA

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ABSTRACT

When analysts provide forecasts of both earnings and operating cash flow, they also implicitly provide a forecast of total operating accruals. We posit that this increases the transparency and the expected costs of accrual manipulations used to manage earnings. As a consequence, we predict and find that accrual quality improves and firms' propensity to meet or beat earnings benchmarks declines following the provision of cash flow forecasts. We also predict and find that firms turn to other benchmark-beating mechanisms, such as real activities manipulation and earnings guidance in response to the provision of cash flow forecasts.

1. Introduction

When analysts provide forecasts of both earnings and operating cash flow, they also implicitly provide a forecast of total operating accruals. Thus, cash flow forecasts enable parties external to the firm to more readily decompose an earnings surprise into the portion attributable to unexpected cash flows and a portion attributable to abnormal accruals. We posit that cash flow forecasts increase the transparency of accrual manipulations used to manage earnings. As the transparency of opportunistic earnings management increases, so does the likelihood of restatements and regulatory interventions, which in turn, increases the expected costs to the firm and to managers of engaging in opportunistic earnings management. Management is less likely to resort to accrual manipulation as the expected costs of engaging in earnings management through accruals increases. Thus, we posit that by increasing the transparency of accrual manipulations, analysts' provision of cash flow forecasts serves as an effective earnings management constraint that increases the quality of reported accruals. We also predict that by reducing accrual manipulations, the provision of cash flow forecasts will reduce the likelihood that firms

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* Corresponding author.
E-mail addresses: john.mcinnis@mccombs.utexas.edu (J. McInnis), daniel-collins@uiowa.edu (D.W. Collins).

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will meet or beat earnings targets. In addition, we hypothesize as it becomes more costly to manage earnings through accruals, managers are likely to shift to other mechanisms in an effort to achieve earnings benchmarks. Thus, we predict that the incidence of real activities management and expectations management will increase in the presence of cash flow forecasts.

To test these hypotheses, we conduct within-firm inter-temporal change tests for firms before and after analysts began providing cash flow forecasts and we benchmark our findings against a control sample. We identify a sample of firm-years for which I/B/E/S provided both earnings and operating cash flow forecasts (treatment sample) and a propensity-score matched sample (using factors prior research has shown to be related to analysts' cash flow forecasts) of firm-years without cash flow forecasts (control sample). Our analysis reveals a significant decline in the magnitude of positive and absolute performance-adjusted abnormal accruals, and a better mapping of accruals into cash flows after analysts begin providing cash flow forecasts compared to the period prior to when those forecasts were first issued. We do not observe a similar increase in accrual quality for the control firms. We also find that after the provision of cash flow forecasts, firms place greater emphasis on some forms of real transaction management and downward earnings guidance in an attempt to beat analysts' earnings expectations. Despite these efforts, we find that firms are less likely to meet earnings targets after analysts begin issuing cash flow forecasts relative to before analysts' provision of cash flow forecasts. We do not observe a similar decline in the tendency to meet or beat earnings expectations for the control firms. Collectively, our propensity score matching procedure, inter-temporal change analyses using a difference-in-differences design, and findings that relate changes in income-increasing accruals to changes in real transaction management and earnings guidance allow us to draw inferences about the direction of causation, which help mitigate endogenous self-selection concerns that plague purely cross-sectional research designs. Our results provide evidence that the provision of cash flow forecasts increases the transparency of accrual manipulations and acts as a deterrent to opportunistic earnings management through accruals, thereby enhancing accrual quality.

We also consider two competing explanations for our benchmark beating results. The first is that the issuance of cash flow forecasts portends a decline in economic performance of firms and this is why we observe a decline in the meet-or-beat tendencies of our treatment sample over time. The second is that once analysts issue cash flow forecasts, firms focus on meeting their cash flow targets at the expense of their earnings targets. We perform a variety of tests and find no evidence that either of these explanations is driving our results.

Our findings contribute to the extant literature in several ways. First, we provide evidence that analysts' cash flow forecasts serve as a deterrent to accrual manipulation, which increases the quality of accruals and reduces firms' tendency to engage in myopic meet-or-beat behavior that is often value destroying (Jensen, 2005). This finding is of interest to investors and regulators who share an interest in fostering honest, transparent reporting and reducing management actions that lead to costly restatements and regulatory interventions.

Our research also sheds light on the role of alternative mechanisms for deterring earnings management. Recent research indicates that the Sarbanes-Oxley Act led to reduced earnings management through accruals (Cohen et al., 2008) and that annual audits help curb benchmark-beating behavior (Brown and Pinello, 2007). But these legislative mandates and regulatory monitoring mechanisms are costly to firms and ultimately to shareholders. Analysts' cash flow forecasts, on the other hand, are provided at relatively low cost to investors. Thus, while prior literature demonstrates that costly regulatory mechanisms improve earnings quality, our study identifies a relatively inexpensive provision of information by intermediaries that serves to deter earnings management through accruals and positively impacts accrual quality. Prior research contends that cash flow forecasts facilitate market participants' assessment of firm solvency (DeFond and Hung, 2003). Our findings suggest that cash flow forecasts play an even broader role in the financial reporting process by serving as a disciplining mechanism that directly affects managers' opportunistic reporting behavior.

Finally, our findings extend the literature that examines the link between accrual management and beating analyst forecasts. While some studies find little evidence of a link (Dechow et al., 2003; Phillips et al., 2003), other studies find some evidence that accrual manipulation contributes to the observed discontinuity of earnings surprises around zero (Payne and Robb, 2000; Ayers et al., 2006). Our study suggests that cash flow forecasts lead to an improvement in earnings quality and to a decrease in the likelihood of meeting analysts' earnings forecasts. Thus, we offer evidence (albeit indirect) that accrual manipulation plays some role in the disproportionate number of firms that report positive earnings surprises.

The remainder of our paper is organized as follows. Section 2 reviews prior literature and develops our hypotheses. Section 3 describes our sample and methodology, and Section 4 presents descriptive statistics and results of our empirical tests. Section 5 considers alternative explanations for our benchmark beating results. Section 6 concludes and offers directions for future research.

2. Prior research and hypotheses development

2.1. The costs of accrual manipulation

Prior research provides evidence that earnings restatements and Securities and Exchange Commission (SEC) Accounting and Auditing Enforcement Releases (AAERs) impose significant costs on firms' shareholders and on managers responsible for the financial misconduct. Restatements and SEC AAERs are associated with significant declines in firm value (Karpoff et al., 2008a; Feroz et al., 1991; Dechow et al., 1996; Beneish, 1999; Palmrose et al., 2004), and significant increases in firms' cost of equity (Hribar and Jenkins, 2006) and CEO turnover (Karpoff et al., 2008b; Agrawal and Cooper, 2009).

Karpoff et al. (2008a) estimate that for each dollar that a firm misleadingly inflates its market value through inflated earnings, on average, it loses this dollar plus an additional $3.08 when the accounting misconduct is revealed through SEC or Department of Justice (DOJ) enforcement actions. They estimate that roughly two-thirds of this loss in value reflects ‘‘reputational loss’’—the decrease in the present value of the firm's future cash flows that result as investors, creditors, customers and suppliers change the terms of trade for doing business with the firm. Karpoff et al., conclude that financial misrepresentation, if detected, is a particularly costly activity because it undermines the firm's credibility with external parties.

In addition to personal wealth decreases that managers suffer from lost value in the firm's shares they hold, managers face other personal costs when financial misconduct is revealed. Agrawal and Cooper (2009) find strong evidence that following restatements, firms experience greater turnover of CEOs, CFOs and other top management compared to a sample of control (non-restating) firms from the same industry. Karpoff et al. (2008b) track the fortunes of 2206 managers identified as responsible parties in 788 SEC and DOJ enforcement actions for financial misrepresentation from 1978 through September 2006 and find that 93% lose their jobs by the end of the regulatory enforcement period. The majority of these managers are explicitly fired. Culpable managers also bear substantial financial losses through fines and restrictions on their future employment. SEC fines of individuals implicated in financial fraud average $8.3 million and roughly 40% of the executives have been barred from serving as an officer or director of another public company registered with the SEC.

Managers can opportunistically manage earnings either through real transactions management (e.g., cutting back on R&D or advertising expenditures) or through accruals manipulation. While firms are generally free to engage in real transaction management without attracting intervention of auditors or regulators, firms increase the risk of restatements and SEC investigation when managers engage in accruals manipulation to manage earnings because, ex post, these accrual manipulations may be deemed by regulators to fall outside the boundaries of GAAP. The expected costs of restatements and regulatory intervention, outlined earlier in this section, increase as accrual manipulation becomes more visible.

2.2. Cash flow forecasts and the transparency of accrual manipulations

The dissemination of cash flow forecasts by analysts is relatively recent phenomenon in the U.S. Forecasts of operating cash flow for U.S. firms began appearing in the I/B/E/S detail files in 1993, and have increased in prevalence over the last decade. For example, we find in untabulated results that the proportion of US firms in I/B/E/S (with data available in COMPUSTAT and CRSP) for which analysts predicted both earnings and operating cash flows was roughly 1% in 1993, 12% in 1999, and 39% in 2003.

Observing a cash flow forecast in I/B/E/S is a joint product of analysts forecasting cash flows, analysts making those forecasts available to I/B/E/S and I/B/E/S disseminating those forecasts. DeFond and Hung (2003) argue that analysts' cash flow forecasts are demand driven. They posit and find that analysts tend to forecast cash flows for firms where accounting, operating and financing characteristics suggest that cash flows are useful in interpreting earnings and assessing firm viability. Because cash flow forecasts are endogenously determined, it is important to control for firm-specific characteristics associated with the provision of cash flow forecasts. We do this in two ways: (1) we conduct intertemporal change analysis, effectively using each firm as its own control; and (2) by identifying a sample of control firms that are selected by using a propensity-score matching procedure based on the determinants of cash flow forecast identified in DeFond and Hung (2003).

Both I/B/E/S documentation and DeFond and Hung (2003) indicate that analysts' cash flow forecasts do not merely represent crude manipulations of earnings, such as EBITDA; rather, they represent relatively sophisticated projections of cash flows from continuing operations. Thus, when analysts forecast both earnings and cash flows, they also implicitly forecast total operating accruals. Given both an earnings and a cash flow forecast, outsiders can readily decompose an earnings surprise into the portion attributable to cash flow and the portion attributable to accruals. Therefore, cash flow forecasts provide a readily available and objective benchmark for assessing abnormal accrual manipulations in either a positive (income-increasing) or negative (income-decreasing) direction.

2.3. Prior research on the predictive ability and disciplining implications of cash flow forecasts

Several recent papers investigate the predictive ability and disciplining implications of analyst and management cash flow forecasts. Givoly et al. (2009) compare the accuracy of analysts' cash flow and earnings forecasts and find that analysts' cash flow forecasts are less accurate and of lower quality than earnings forecasts.[1] However, they do not directly test whether the provision of cash flow forecasts improves analysts' ability to forecast earnings (this question is addressed in the Call et al. (2009) paper discussed below). Givoly et al. (2009) also find that unexpected accruals based on comparing analysts' implied accruals forecast[2] and actual accruals have very low power in detecting (predicting) earnings management. They interpret this result to imply that cash flow forecasts and implied accrual forecasts are of low quality, and consequently are of marginal value.

[1] In their comparison of the accuracy of analysts' cash flow and earnings forecasts, Givoly et al. (2009) do not fully control for the fact that operating cash flows are inherently more volatile than earnings, and that there is less management guidance for cash flow forecasts compared to earnings forecasts. Both of these factors contribute to higher accuracy of earnings forecasts relative to cash flow forecasts.

[2] Analysts' implied accruals forecast is the difference between the consensus earnings forecast and cash flow forecast for each firm.

It is important to note that in the Givoly et al. (2009) study, the trigger for identifying instances of earnings management is when the standardized absolute value of analyst-based unexpected accruals exceeds values of 1.0, 1.5 and 2.0. Hribar and Nichols (2007) caution against using absolute value of abnormal accruals as a proxy for earnings management. Moreover, if earnings management is achieved through relatively small accrual manipulations, e.g., when firms are managing accruals to achieve an earnings benchmark, these instances would go undetected using the Givoly et al. (2009) metric. Finally, the Givoly et al. (2009) test implicitly assumes that the provision of cash flow forecasts has *no effect* on firms' earnings management behavior. If, as we posit, analysts' cash flow forecasts act to deter firms from engaging in earnings management through accruals, then one would *not* expect to find analysts' implied accrual forecast errors to be predictive of earnings management. To understand why, assume that analyst-based implied accrual forecasts allow regulators to perfectly identify when earnings are being manipulated through accruals. If regulator detection of earnings management is costly to firms and to management as prior research suggests, then knowing that accrual manipulations can be readily detected by regulators will deter firms (managers) from using accruals to manipulate earnings. Accordingly, one would not expect to find a strong positive association between analyst-based accrual forecast errors and accruals-based earnings management.

Call et al. (2009) investigate whether analysts' earnings forecasts are more accurate when they also issue cash flow forecasts. The authors reason that analysts are more likely to attend to the individual components of earnings (cash flows and accruals) and have a better grasp of the time-series properties of earnings and its components when they forecast both earnings and cash flows. Consistent with their predictions, they find that analysts' earnings forecast that are accompanied by cash flow forecasts are more accurate than those not accompanied by cash flow forecasts.

Call (2008) posits that when analysts issue cash flow forecasts, they serve an important monitoring role over firms' reported cash flow information, which improves its predictive ability. Consistent with this prediction, Call finds that the ability of reported cash flows to predict future cash flows is greater for firms whose analysts issue cash flow forecasts, and improves when analysts begin forecasting cash flows. Call also finds that firms' abnormal operating cash flows are significantly smaller in the years immediately after analysts' cash flow forecasts are initiated. Although not tested directly, this finding suggests that analysts' cash flow forecasts deter managers from engaging in earnings management through real activities management in ways that affect cash flows. We take a closer look at this issue later in this paper.

Further evidence that cash flow forecasts act to constrain opportunistic earnings management is provided by Wasley and Wu (2006). They predict that when management issues cash flow forecasts, they pre-commit to a certain composition of earnings in terms of cash flows versus accruals, thus reducing the degrees of freedom in earnings management. Consistent with this prediction, they find that when managers are managing earnings upward by manipulating discretionary accruals, they are less likely to issue a management cash flow forecast because doing so would draw attention to the upward manipulation in earnings.

2.4. Hypothesis on the effect of analysts' cash flow forecasts on earnings (accrual) management

We posit that analysts' provision of operating cash flow forecasts makes manipulation of accruals more transparent, thereby increasing the expected costs to firms and managers of engaging in earnings management through accrual manipulation. As the expected costs of accrual manipulations increase, managements' incentives to do so are expected to decrease. Thus, we posit that by increasing the transparency of accrual manipulations, analysts' provision of cash flow forecasts serve as an effective earnings management constraint that increases the quality of reported accruals. Accordingly, we expect firms for which analysts provide cash flow forecasts to exhibit higher quality accruals (i.e., smaller positive, negative and absolute abnormal accruals and less accrual noise) following the provision of cash flow forecasts relative to before these forecasts were issued. We formalize this hypothesis as H1 (stated in the alternative form):

H1. Earnings management through accruals decreases after the provision of cash flow forecasts.

2.5. Cash flow forecasts and firms' choice of alternative benchmark beating mechanisms

Prior research suggests that managers have strong incentives to beat earnings benchmarks. A survey by Graham et al. (2005) indicates that over 80% of the financial executives surveyed agreed or strongly agreed that capital market-based incentives are a major reason why their companies try to meet earnings benchmarks. Over 74% of the financial executives surveyed agreed or strongly agreed that "meeting earnings benchmarks helps us convey our future growth prospects to investors." Consistent with these survey results, DeGeorge et al. (1999) document an "unusual pileup" of observations in the empirical distribution of earnings surprises at and just above zero: too many firms seem to just meet or beat analysts' earnings forecasts relative to the number of firms that just miss these forecasts. Brown and Caylor (2005) find that: (1) the tendency of firms to avoid reporting negative earnings surprises has been increasing over time and (2) analysts' earnings expectations now represent the most important threshold firms seek to exceed.[3]

A variety of studies have examined whether accrual management is associated with the disproportionate number of reported earnings surprises equal to a few cents per share or less. In general, the findings have been mixed. Some studies (Payne and Robb, 2000; Matsumuto, 2002; Ayers et al., 2006) find that accrual management is related to meeting or beating

[3] Other thresholds investigated in the literature involve avoiding losses and earnings declines—see Burgstahler and Dichev (1997) for example.

analysts' earnings forecasts, while other studies fail to find such an association (Schwartz, 2004; Phillips et al., 2003). We argue that the presence of cash flow forecasts makes accrual manipulations to achieve EPS targets more transparent. This transparency reduces the stock price benefit of an accrual manipulating strategy (Melendrez et al., 2008), and also potentially increases its cost (e.g., through a higher probability of regulatory or stockholder scrutiny). Thus, we contend that analysts' cash flow forecasts serve to constrain firms in their ability to manage accruals to meet earnings targets.

When firms' ability to manage earnings through accruals is constrained they are likely to shift to other mechanisms to meet earnings benchmarks. Roychowdury (2006) finds that firms manipulate real activities, such as cutting discretionary expenditures, raising production levels, or offering excessive discounts to generate higher earnings. Prior research suggests that firms shift to these real activities management techniques to manage earnings when the costs of managing earnings through accruals increases (Cohen et al., 2008; Cohen and Zarowin, 2010). In addition, managers can guide analysts' expectations downward in order to meet EPS forecasts (Matsumoto, 2002, Bartov et al., 2002). If cash flow forecasts constrain accrual management, it is reasonable to expect that firms will turn to these alternative benchmark beating mechanisms in the face of cash flow forecasts. Thus, we predict that the incidence of real activities management and expectations management will increase in the presence of cash flow forecasts. We formalize these hypotheses as H2 and H3 (stated in the alternative form):

H2. Real activities earnings management increases after the provision of cash flow forecasts.

H3. Downward expectations management (guidance) increases after the provision of cash flow forecasts.

These alternative benchmark beating mechanisms are not costless substitutes for accrual management, however. Managing expectations downward can lead to negative stock price reaction as analysts' forecasts are revised accordingly (e.g., Stickel, 1991), and may also lead to a potential lack of management credibility with investors in the future. Real transactions management, such as cutting current discretionary expenditures like R&D, can lead to poorer future operating performance (Bhojraj et al., 2009) and adversely affect firm value.

In addition to cost considerations, not all firms will necessarily find these alternative mechanisms for meeting earnings targets equally effective. For example, some firms may have more success than others at guiding analysts' earnings expectations, based either on greater credibility from prior analyst interactions, or because these firms share a greater actual or potential economic bond with analysts and their brokerages (e.g., the firms are net equity issuers—see Richardson et al., 2004). Finally, some firms may be unable to cut discretionary expenditures in a timely fashion if resource commitments have already taken place. For example, it may be impossible for a firm to meaningfully cut R&D expenditures late in the year to avoid a negative earnings surprise if the majority of its R&D budget has already been expended. In short, even if firms, on average, increase their level of expectations management or cut discretionary spending in the face of cash flow forecasts, such activities are costly. Therefore, they may not serve as perfect substitutes for accrual manipulation to achieve earnings benchmarks. Accordingly, we expect the provision of cash flow forecasts will, on average, serve to constrain firms' ability to meet earnings targets. We formalize this hypothesis as H4 (stated in the alternative):

H4. The probability of meeting or beating analysts' earnings targets decreases after the provision of cash flow forecasts.

Hypothesis H4 is made under the maintained hypothesis that analysts' behavior with respect to forecasting earnings does not change after the provision of cash flow forecasts. We consider alternative predictions if this assumption does not hold when discussing the meet-or-beat results below.

3. Sample and methodology

In this section, we describe our sample and the methodology used to test the hypotheses developed above. Section 3.1 briefly describes our data sources, and Section 3.2 provides an overview of our design, along with a detailed description of our tests of H1 through H4. We use a difference-in-differences design to test our predictions by comparing intertemporal differences for treatment (cash flow forecast) and control (non-cash flow forecast) samples. This design allows us to infer changes in the following characteristics after the issuance of cash flow forecasts: accrual quality (H1); real activities earnings management (H2); downward earnings guidance (H3); and the tendency to meet EPS targets (H4).

3.1. Data

We initially select all annual EPS forecasts for U.S. firms on the I/B/E/S detail file from 1993 to 2004. We use annual data because the majority of cash flow forecasts are provided on an annual basis. Because we use a variety of accounting variables in the regressions that follow, we also eliminate observations lacking necessary data from COMPUSTAT and CRSP. There are 5237 firm-years with both an EPS forecast and a cash flow per share forecast that meet our data requirements over our sample period compared to 32,308 firm-years with only an EPS forecast.

3.2. Methodology

Our difference-in-difference design is implemented in several steps. First, for each firm with a cash flow forecast in our sample period, we identify the first year in which analysts' cash flow forecasts appear in the I/B/E/S detail file (the "initial" year). We then select all observations for each firm in the three years prior to this initial year. These observations comprise our pre-cash flow forecast (pre-CF) sub-sample. We also select all available observations for the two years subsequent to this initial year for each firm, with the requirement that cash flow forecasts exist in these subsequent years. Observations for the initial and subsequent two years for each firm comprise our post-cash flow forecast (post-CF) sub-sample.[4]

The choice of a 3-year window for the pre-CF and post-CF sub-periods is somewhat arbitrary and reflects a tradeoff between selecting a window long enough to allow firms' earnings management choices to adjust to the implications of cash flow forecasts, yet short enough to avoid picking up other potential economic events common to all sample firms that could impact earnings quality measures. Our pre-CF sub-sample contains 3965 observations, with the median (and mode) number of observations per firm equaling three. Our post-CF sub-sample contains 3266 observations, with the median (and mode) number of observations per firm equaling two. Together, these 7231 observations comprise our "treatment" sample.

We utilize a control sample to help ensure that any inter-temporal changes in accrual quality, real activities management, downward earnings guidance and benchmark-beating that we document for the CF forecasting (treatment) sample are not common to all firms over the sample period. We identify a sample of firms for which analysts do not forecast cash flows that are similar, along multiple relevant dimensions, to firms for which analysts do forecast cash flows. To identify control firms, we use a propensity-score matching procedure (Rosenbaum, 2002; Rosenbaum and Rubin, 1983; Armstrong et al., 2010; Gassen and Skaife, 2009). For each "initial" firm-year in our treatment sample described above, we select a matching firm (without a cash flow forecast) in the same year that has the closest "propensity score". This propensity score is the predicted value from a logit regression of the incidence of cash flow forecasts on the determinants identified by DeFond and Hung (2003) (See Appendix A).[5] Propensity-score matching assumes that any unobserved factors not included as determinants in the propensity model are random across samples and have no impact on the outcomes of interest. In the context of our difference-in-differences design, this assumption would be violated if, for instance, analysts are more likely to issue cash flow forecasts for firms expected to experience an improvement in earnings quality and a decline in benchmark beating relative to other firms. While we cannot definitively rule out this possibility, we have no reason to suspect such a phenomenon is at work.

Once we obtain propensity-score matches, we then look three years forward and back to construct pseudo pre-CF and post-CF periods for each control firm. Although control firms have no true "event year" like our treatment firms, this process yields a control sample with pre-CF and post-CF periods that have a similar dispersion in calendar time to the periods that comprise our treatment sample. To maintain the statistical independence of our tests, we allow a matching firm-year to be used only once. If a matching firm-year is the best match (based on propensity score and year) for more than one cash flow forecast firm-year, we break the tie by selecting the match with the smallest absolute difference in propensity score. In addition, matched firms are only retained if they do not have a cash flow forecast in either of the two years after the initial matching year. Our control sample consists of 6198 firm-year observations.

3.2.1. *Accrual quality tests*

We test the prediction that cash flow forecasts deter accrual manipulation (H1) by examining inter-temporal shifts in two measures of accrual quality. We employ more than one measure because little consensus exists as to which accrual quality metric is preferable. Our first measure of accrual quality is abnormal accruals as defined by the forward-looking, modified Jones model (Dechow et al., 2003). The definitions and data sources for all variables used throughout our tests are provided in Appendix C. We estimate the following model by year and 2-digit SIC code, for all observations on COMPUSTAT from 1993 to 2004:

$$Accruals_t = \alpha + \beta_1((1+k)\Delta Sales_t - \Delta Receivables_t) + \beta_2 PPE_t + \beta_3 Accruals_{t-1} + \beta_4 SalesGrowth_t + \varepsilon_t \tag{1}$$

All variables are scaled by average total assets, except sales growth which is scaled by lagged sales (see Dechow et al., 2003 for further estimation details). Residuals from Eq. (1) serve as our measure of abnormal accruals for each firm-year in our sample.

We test for temporal shifts in average abnormal accruals by pooling together our treatment and control samples and estimating the following regression:

$$ABNACC_t = \alpha + \beta_1 TREAT_t + \beta_2 POST\_CF_t + \beta_3 POST\_CF_t * TREAT_t + \beta_4 ROA_t + \beta_5 ROA_t * TREAT_t + \varepsilon_t \tag{2}$$

where *ABNACC* is either the positive, negative, or the absolute value of abnormal accruals. *TREAT* is an indicator variable set to 1 if the observation belongs to the treatment sample, and zero otherwise. *POST_CF* is an indicator variable set to 1 if an observation belongs to the post-CF forecast period in either sample, and zero if the observation falls in the pre-CF forecast period. *ROA* is income before extraordinary items scaled by average total assets. We include *ROA* in the regression to control for differences in performance across the two samples because prior research documents a relation between abnormal

[4] DeFond and Hung (2003) indicate that I/B/E/S attempts to distribute all cash flow forecasts received from contributing analysts to its clients. However, it is possible that the year in which the first cash flow forecast for a given firm appears in the I/B/E/S tapes may not necessarily correspond to the first year a particular analyst included a cash flow forecast in a research report for that firm. Even so, dissemination of cash flow forecasts by I/B/E/S certainly makes them more public and should have an effect on market expectations. In any event, if our methodology fails to accurately identify the period before and after market participants obtain cash flow forecast information, this should bias against findings results consistent with our predictions.

[5] Our results are qualitatively similar if we select matching firms on the basis of size and industry (to neutralize industry differences across samples), or if we include industry indicator variables in our empirical tests using our propensity-score matched sample.

accruals and performance (e.g., Dechow et al., 1995). Additionally, Kothari et al. (2005) offer evidence that controlling for ROA reduces the probability of Type I error in earnings management studies where performance differences are not part of the hypotheses being tested.

Our interest in Eq. (2) centers on β_2 and β_3. $\beta_2+\beta_3$ (β_2) measures the incremental change in abnormal accruals for the treatment (control) sample in the post-CF forecast period relative to the pre-CF forecast period. Therefore, β_3 is the incremental shift in abnormal accruals unique to treatment firms. Consistent with our conjecture that the provision of cash flow forecast will deter both income-increasing and income-decreasing earnings management, we expect β_3 and $\beta_2+\beta_3$ to be negative for positive and absolute values of abnormal accruals, and positive for negative abnormal accruals for the treatment sample. That is, we expect the average magnitude of positive, negative and absolute value of abnormal accruals to become smaller if the provision of cash flow forecasts constrains managers opportunistic accruals manipulations.

Our second measure of accrual manipulation involves a measure of accrual noise in the spirit of Dechow and Dichev (2002). Within both our treatment and control samples, we estimate the following regression separately for the pre-CF and post-CF periods:

$$Accruals_t = \alpha + \beta_1 CFO_{t-1} + \beta_2 CFO_t + \beta_3 CFO_{t+1} + \varepsilon_t \tag{3}$$

All variables are scaled by average total assets. We compute the difference in the estimate of overall residual variance, $s^2(\varepsilon)$, from Eq. (3) for the pre-CF and post-CF periods for both our treatment and control samples. Higher quality accruals are expected to map better into past, present and future cash flows. Thus, observations with noisier (lower quality) accruals will exhibit higher residual variances, $s^2(\varepsilon)$ from Eq. (3). If cash flow forecasts deter opportunistic earnings management, we expect $s^2(\varepsilon)$ to be smaller in the post-CF period relative to the pre-CF period for treatment firms. We make no predictions relative to the change in $s^2(\varepsilon)$ for control firms. We test the statistical significance of differences in estimates of residual variance using an *F*-test described in Appendix B.

3.2.2. Testing for shifts in real activities management

To test the prediction that the use of alternative benchmark-beating mechanisms increases after the provision of cash flow forecasts, we first examine whether firms exhibit greater evidence of managing earnings through real activities manipulation after analysts begin providing cash flow forecasts. Following Roychowdury (2006), we measure real activities manipulation as abnormal levels of discretionary expenditures, production, and cash flows from operations. We estimate abnormal discretionary expenditures (*ABNDISC*) as the residuals from the following regression estimated by year and 2-digit SIC code, for all observations on COMPUSTAT from 1993 to 2004:

$$Disc.Expenditures_t = \alpha(1/Assets_{t-1}) + \beta_1 Sales_t + \varepsilon_t \tag{4}$$

All variables are scaled by lagged total assets. We measure discretionary expenses as R&D plus advertising plus SG&A. H2 predicts that discretionary expenditures of treatment firms should be lower after the provision of cash flow forecasts. Thus, we expect *ABNDISC* to be more negative in the post-CF forecast period compared to the pre-CF period for our treatment firms. We make no prediction for our control firms.

We estimate abnormal production (*ABNPROD*) as the residuals from the following regression estimated for the COMPUSTAT population by year and two digit industry:

$$Prod.Costs_t = \alpha(1/Assets_{t-1}) + \beta_1 Sales_t + \beta_2 \Delta Sales_t + \beta_3 \Delta Sales_{t-1} + \varepsilon_t \tag{5}$$

Production costs equal cost of goods sold plus the change in inventory. Following the arguments in Roychowdury (2006), H2 predicts that abnormal production will be higher after the provision of cash flow forecasts as firms try to increase earnings by allocating a larger portion of fixed overhead costs to over-produced units in inventory. Thus, we expect *ABNPROD* to be more positive in the post-CF forecast period compared to the pre-CF period for our treatment firms. We make no prediction for our control firms.

We estimate abnormal operating cash flows (*ABNCFO*) as the residual from the following regression estimated by year and two digit industry:

$$CFO_t = \alpha(1/Assets_{t-1}) + \beta_1 Sales_t + \beta_2 Sales_{t-1} + \varepsilon_t \tag{6}$$

The logic behind this specification is that firms may try to boost sales and earnings by offering higher discounts to customers or by channel stuffing near the end of the year. However, these real transaction management actions will lower the amount of cash collected per dollar of sales in the current period. This is expected to result in negative abnormal cash flows in Eq. (6). To avoid the offsetting effects that changes in discretionary expenditures can have on abnormal CFO (Cohen and Zarowin, 2010), we add discretionary expenditures to cash flow from operations before estimating Eq. (6). H2 predicts that abnormal cash flows of treatment firms should be lower after the provision of cash flow forecasts compared to the pre-CF period as firms try to ease credit terms and offer discounts to generate higher sales and profits. We make no prediction for our control firms.

3.2.3. Testing for shifts in expectations management

To estimate downward expectations management, we follow the methodology of Matsumoto (2002). We estimate a time-series model of EPS changes (adapted for annual data) to assess the extent to which analysts forecasts for a given firm-year are lower than expected. Specifically, we estimate the following regression using all available data in I/B/E/S and CRSP from 1990 to 2004:

$$\Delta EPS_t = \alpha + \beta_1 \Delta EPS_{t-1} + \beta_2 CUMRET_t + \varepsilon_t \tag{7}$$

where CUMRET is the buy-and-hold, market adjusted return for firm *i*, cumulated beginning the month after the earnings announcement for time $t-1$ and ending the month before the earnings announcement for time *t*. All ΔEPS variables are scaled by lagged stock price. Eq. (7) is an attempt to model the current change in EPS as a function of the last year's change in EPS plus current year news imbedded in stock returns. We estimate Eq. (7) annually and use the coefficient estimates to generate the expected change in EPS for the current year for all observations with available data in both treatment and control samples. We then add this expected change to the prior year EPS to obtain the "expected" forecast of current EPS. We create a dummy variable for downward expectations management, *EXPMGMT*, equal to 1 if the last actual forecast of EPS prior to the earnings announcement date is less than the "expected" forecast, and zero otherwise.

To test whether analysts provision of cash flow forecasts increases firms' propensity to engage in downward expectations management (H3) we estimate the following logistic regression model:

$$\begin{aligned} Prob(EXPMGMT_t = 1) = \alpha &+ \beta_1 POST\_CF_t + \beta_2 SIZE_t + \beta_3 MTB_t + \beta_4 RD_t + \beta_5 LOSS_t \\ &+ \beta_6 LITIGATION_t + \beta_7 LABOR_t + \beta_8 ISSUE_t + \beta_9 RELEVANCE_t + \varepsilon_t \end{aligned} \tag{8}$$

POST_CF is set equal to 1 if the observation comes from the post-CF period and zero otherwise. H3 predicts that as firms' ability to manage earnings upward through accruals becomes more constrained following the provision of cash flow forecasts, their propensity to guide analysts' earnings expectations downward is likely to increase. Accordingly, we expect β_1 to be positive for the treatment sample. We make no prediction for the control sample. The remaining variables are controls based on the findings of Matsumoto (2002) and are defined in detail in the table footnotes. Firms with higher market values (*SIZE*), market-to-book ratios (*MTB*), R&D intensity (*RD*), higher litigation risk (*LITIGATION*), higher labor intensity (*LABOR*), and greater value relevance of earnings (*RELEVANCE*) have greater incentives to meet earnings targets, so we expect these characteristics to be positively associated with downward guidance. Firms with losses (*LOSS*) have less value relevant earnings (i.e., leading to less incentive to manage downward), but also have poor prospects (which could lead to lower expectations), so we do not make a prediction for the sign on this variable. Finally, we augment the variables from Matsumoto with a dummy variable for equity issuance (*Issue*), given the findings of Richardson et al. (2004), who link expectation walk-downs to equity issuances. We expect a positive loading on this variable. To avoid cumbersome interactions, we estimate Eq. (8) separately for our treatment and control samples.

3.2.4. *Linking changes in accruals management to alternative benchmark-beating mechanisms*

In an effort to more directly link changes in discretionary accruals following the provision of cash flow forecasts to increases in real activities management and earnings guidance, we estimate the following cross-sectional logit model for treatment and control firms separately:

$$Prob(CUTACRR_t = 1) = \alpha + \beta_1 ABNDISC_t + \beta_2 ABNPROD_t + \beta_3 ABNCFO_t + \beta_4 EXPMGMT_t + \varepsilon_t \tag{9}$$

CUTACCR is a dummy variable equal to 1 if a firm cuts (reduces) its average level of positive abnormal accruals from the pre-CF to the post-CF period. All other variables are as previously defined. This logit model is estimated using data from the post-CF period (after the issuance of cash flow forecasts). We expect treatment firms that reduce their income-increasing abnormal accruals following the provision of cash flow forecasts to have lower (more negative) abnormal discretionary expenditures and abnormal operating cash flows, higher abnormal production and are more likely to engage in downward expectations management. Accordingly, we expect β_1 and β_3 to be negative and β_2 and β_4 to be positive for treatment firms. We make no predictions for control firms.

3.2.5. *Testing for shifts in benchmark beating*

Finally, to test our prediction involving the incidence of benchmark beating following the provision of cash flow forecasts (H4), we use logistic regression to estimate the probability that a firm will meet or beat analysts' earnings expectations, given a vector of explanatory variables. Our dependent variable, meet or beat (*MB*), is a dummy variable equal to 1 if the firm's reported earnings equals or exceeds analysts' earnings forecasts (i.e., EPS surprise is zero or positive), and zero otherwise (i.e., EPS surprise is negative). We define earnings surprises as actual earnings per I/B/E/S less the last available analyst forecast of earnings prior to the annual earnings announcement date. Again, to avoid cumbersome interactions, we estimate our logistic regression separately for our treatment and control samples. Our variable of interest, post-cash flow forecast period (*POST_CF*), is a dummy variable equal to 1 if the firm-year in question falls in the post-CF period, and zero otherwise. We also include a set of control variables (explained in more detail below) as covariates. Specifically we estimate:

$$\begin{aligned} Prob(MB_t = 1) = \alpha &+ \beta_1 POST\_CF_t + \beta_2 CFO_t + \beta_3 ACC_t + \beta_4 CAPINT_t + \beta_5 ALTZ_t + \beta_6 CHOICE_t \\ &+ \beta_7 SIZE_t + \beta_8 BLOAT_t + \beta_9 SHARES_t + \beta_{10} MTB_t + \beta_{11} FOLLOW_t + \beta_{12} PMB_t \\ &+ \beta_{13} REVDOWN_t + \beta_{14} WRITE_t + \beta_{15} LOSS_t + \beta_{16} EARNGROW_t + \varepsilon_t \end{aligned} \tag{10}$$

Estimates from Eq. (10) allow us to assess the effect of cash flow forecasts on the probability that a firm will meet or beat analysts' earnings forecasts (i.e., zero or positive forecast error) versus the alternative of missing analysts' forecasts (i.e., negative forecast error). H4 predicts that the coefficient on *Post_CF* will be negative for our treatment sample. We make no predictions for our control sample.

Our vector of controls includes variables designed to predict whether firms will meet or beat their earnings targets or variables that are known to be associated with the provision of cash flow forecasts. We include cash flow from operations (*CFO*) because this is a variable that prior research (Phillips et al., 2003; Ayers et al., 2006) has utilized as a measure of performance to help explain why firms meet their earnings targets.[6] We also include five of the economic determinants of cash flow forecast provision identified by DeFond and Hung (2003): (1) accruals (*ACC*), (2) capital intensity (*CAPINT*), (3) heterogeneity of accounting choices (*CHOICE*), (4) Altman's *Z*-score (*ALTZ*) and (5) market value (*SIZE*) [see Appendix A].[7] We include these controls to guard against the possibility that shifts in these variables may be correlated with firms' tendencies to meet or beat analsyts' forecasts (*MB*). Firms in poor financial condition are expected to have a harder time meeting earnings expectations relative to other firms. Thus, we expect a positive loading on Altman's *Z*-score (*ALTZ*).[8] Prior research (Barton and Simko, 2002, Matsumoto, 2002) has shown that *SIZE* is positively related to meeting earnings targets, so we expect a positive loading on this variable. We do not predict the signs on the remaining determinants of cash flow forecast provision.

We also include additional control variables based on the findings of Barton and Simko (2002) that firms with "bloated" balance sheets (history of positive cumulative accruals) may be less able to manage accruals upward to meet current earnings targets. Bloat is defined as net operating assets (essentially total assets less cash) scaled by sales. Firms with a large number of shares outstanding, all else equal, will have to engage in a larger dollar amount of earnings management to generate a one penny increase in EPS. As a result, we include both net asset bloat (*BLOAT*) and the average number of shares outstanding (*SHARES*) in Eq. (10) and we expect the coefficients on these variables to be negative.

Firms with high growth prospects (high market-to-book (*MTB*) ratio) face greater pressure to meet earnings targets (Skinner and Sloan, 2002) as do firms with a large analyst following (Barton and Simko, 2002). Therefore, we include the *MTB* ratio and the number of analysts following a firm in a given year (*FOLLOW*) in Eq. (10). We expect the coefficients on *MTB* and *FOLLOW* to be positive. Barton and Simko (2002) also demonstrate that firms that meet earnings targets in the prior period are more likely to do so in the current period, so we include a dummy variable (*PMB*) to capture this effect and expect this variable to be positively related to *MB*.

Both Matsumoto (2002) and Bartov et al. (2002) offer evidence that firms manage expectations to "talk-down" analysts in order to meet earnings forecasts. Accordingly, we create a dummy variable, *REVDOWN*, to indicate whether analysts' forecasts have been revised downward during the year. *REVDOWN* is equal to 1 if the last forecast of annual EPS prior to the announcement date is less than the first forecast for that year. Because expectations management is a mechanism for avoiding negative earnings surprises, one might expect *REVDOWN* to be positively related to *MB*. However, downward revisions may also be a sign of bad news for the period and may actually be negatively related to *MB* (Barton and Simko, 2002). Thus, we do not predict the sign of the coefficient on this variable.

Finally, a primary concern when testing for shifts in benchmark beating over time is that shifts in performance before and after the provision of cash flow forecasts may explain firms' propensities to beat earnings targets. Because we include both *CFO* and *ACC* in Eq. (10), we effectively control for differences in ROA. However, we also add the following performance-related dummy variables: *WRITEOFF*, equal to 1 if the firm had asset write downs during the year, and zero otherwise. *LOSS* is set equal to 1 if the firm incurred a loss for the year, and zero otherwise. *EARNGROW* is set equal to 1 if earnings this year grew from last year, and zero otherwise. We expect *WRITEOFF* and *LOSS* to be negatively related to *MB*, while we expect a positive relation between *MB* and *EARNGROW*. In addition to the controls discussed above, we also include year and industry dummies in Eq. (10) to control for year and industry effects.

4. Results

4.1. Descriptive statistics

Table 1 presents means for a variety of variables used in our analysis for both cash flow forecast ("treatment") and matched ("control") samples. Panel A presents means for the two samples in the pre-CF period, while Panel B presents means in the post-CF period. Panel C compares changes in means from the pre- to post-CF periods across samples. To reduce the influence of outliers, all continuous variables have been winzorized at the 1st and 99th percentiles of their respective distributions. In terms of the determinant variables for cash flow forecasts (see Appendix A), Panel A indicates that in the pre-CF period firms with cash flow forecasts are somewhat larger in size, have higher Altman *Z*-scores (better financial health), exhibit slightly more accounting choice heterogeneity and have lower total accruals than matched control firms. The two samples exhibit similar capital intensity. [9] We note that the differences in determinant variables across samples

[6] Phillips et al. (2003) and Ayers et al. (2006) actually use the change in cash flows as a RHS variable. We use the level of cash flow because the distribution of EPS surprises is constructed using the level of net earnings. Our findings are qualitatively similar if we use changes in CFO rather than levels.

[7] Unlike DeFond and Hung (2003), who use the absolute value of accruals, we use the signed value of accruals in our regressions because, together with CFO, this variable constitutes ROA, a basic performance control. Inferences are identical if we use the unsigned value of accruals. We also do not include the sixth determinant identified by DeFond and Hung, earnings volatility, because this is likely a stable characteristic given our relatively short pre- and post-CF periods and we would have limited annual time-series observations in each sub-period to estimate this measure.

[8] Lower Altman's *Z*-scores indicate poorer financial health.

[9] We do not tabulate values for earnings volatility (a determinant variable in Appendix A) in Table 1 because this variable is calculated over the entire sample period and thus does not vary from the pre-CF to the post-CF period.

Table 1
Means of selected variables for firms with cash flow forecasts (treatment) and without cash flow forecasts (control).

Variable	Treatment	Control	Diff.	*p*-value
Panel A: Pre-cash flow forecast period				
CF forecast determinants				
SIZE	6.965	6.028	0.937	< 0.0001
CAPINT	0.970	0.900	0.070	0.2884
ACC	−0.079	−0.069	−0.010	0.0180
ALTZ	6.218	5.555	0.664	0.0046
CHOICE	0.151	0.136	0.015	0.0003
Other variables				
MB	0.699	0.643	0.056	< 0.0001
CFO	0.098	0.033	0.065	< 0.0001
MTB	3.934	3.065	0.870	< 0.0001
BLOAT	1.051	1.381	−0.330	< 0.0001
SHARES	117.748	39.233	78.515	< 0.0001
FOLLOW	11.513	7.427	4.086	< 0.0001
PMB	0.706	0.653	0.053	< 0.0001
REVDOWN	0.542	0.533	0.009	0.4801
WRITEOFF	0.413	0.351	0.062	< 0.0001
LOSS	0.243	0.243	0.000	0.9774
EARNGROW	0.605	0.618	−0.013	0.2991
ABSABNACC	0.071	0.081	−0.010	0.0129
Panel B: Post-cash flow forecast period				
CF forecast determinants				
SIZE	7.118	6.350	0.768	< 0.0001
CAPINT	1.218	1.279	−0.061	0.4526
ACC	−0.082	−0.068	−0.014	< 0.0001
ALTZ	4.602	3.588	1.014	< 0.0001
CHOICE	0.151	0.139	0.012	0.0023
Other variables				
MB	0.664	0.632	0.033	0.0065
CFO	0.105	0.024	0.080	< 0.0001
MTB	3.183	2.855	0.329	0.0009
BLOAT	1.304	1.820	−0.515	< 0.0001
SHARES	161.237	60.499	100.738	< 0.0001
FOLLOW	12.848	7.538	5.310	< 0.0001
PMB	0.697	0.652	0.045	0.0003
REVDOWN	0.532	0.518	0.014	0.2674
WRITEOFF	0.455	0.422	0.033	0.0071
LOSS	0.250	0.287	−0.037	0.0009
EARNGROW	0.633	0.597	0.036	0.0032
ABSABNACC	0.061	0.084	−0.023	< 0.0001
Panel C: Changes from pre to post-cash flow forecast period				
CF forecast determinants				
SIZE	0.153	0.322	−0.169	0.0024
CAPINT	0.248	0.378	−0.131	0.1823
ACC	−0.003	0.001	−0.004	0.3967
ALTZ	−1.616	−1.967	0.351	0.2023
CHOICE	0.000	0.003	−0.003	0.5943
Other variables				
MB	−0.034	−0.011	−0.024	0.0810
CFO	0.007	−0.009	0.015	0.0337
MTB	−0.751	−0.210	−0.541	0.0005
BLOAT	0.253	0.439	−0.185	0.0420
SHARES	43.489	21.266	22.223	0.0053
FOLLOW	1.335	0.111	1.224	< 0.0001
PMB	−0.009	−0.001	−0.008	0.7260
REVDOWN	−0.010	−0.015	0.005	0.7892
WRITEOFF	0.042	0.071	−0.029	0.1003
LOSS	0.007	0.045	−0.037	0.0171
EARNGROW	0.028	−0.021	0.049	0.0051
ABSABNACC	−0.010	0.003	−0.013	0.0150

This table provides mean values of selected variables in the cash flow forecast ("treatment") and non-cash flow forecast ("control") samples. For the treatment sample, we select all annual EPS forecasts for U.S. firms on the I/B/E/S detail file from 1993 to 2004, and retain observations with available data in COMPUSTAT. For each firm with a cash flow forecast in our sample, we identify the first year in which analysts start forecasting cash flows (the "initial" year). We then select all available observations for each firm in the three years prior to this initial year. These observations comprise our "pre" sub-sample. We also select all available observations for the two years subsequent to this initial year for each firm, with the requirement that cash flow forecasts exist in these subsequent years. Observations for the initial and subsequent years for each firm comprise our "post" sub-sample. To construct our control sample, we do the following. For each "initial" firm-year in our treatment sample described above, we select a matching firm (without a cash flow forecast) in the same year that has the closest "propensity score." This propensity score is the predicted value from a logit regression of the incidence of cash flow forecasts on the determinants identified by DeFond and Hung (2003). We then look 3 years forward and back to construct pseudo "pre" and "post" periods for each control firm. This process yields a control sample with "pre" and "post" periods that have a similar dispersion in calendar time to the periods in our treatment sample. Continuous variables have been winsorized at the 1st and 99th percentile of the distributions. See Appendix C for variable definitions and measurements.

are less pronounced in the matching year (the first year of cash flow forecast provision for treatment firms) as shown in Appendix A. In the year matches are formed, only differences in total accruals and Altman *Z* are significantly different from zero.

Interestingly, the additional variables not considered "determinants" of cash flow forecast provision are significantly different across samples as well. Firms with cash flow forecasts have higher operating cash flow, higher market-to-book ratios, less bloat, more shares outstanding, and larger analyst following relative to their matched counterparts. Firms with cash flow forecasts also exhibit a higher incidence of current and prior meet-or-beat tendencies and more frequent asset write offs. Finally, treatment firms have lower absolute (unsigned) abnormal accruals, suggesting less accrual management by firms with cash flow forecasts relative to matched firms.

Panel B reveals similar patterns of differences between the two samples in the post-CF period, except treatment firms have a lower incidence of losses and a higher incidence of positive earnings growth in this period relative to control firms. The relative changes from the pre to the post-CF period reported in Panel C provide evidence consistent with our two main predictions. Consistent with H1, we observe a relative decline in absolute abnormal accruals for treatments firms (p=0.015, one-tailed) after the provision of cash flow forecasts. We also observe a marginally significant decline in meet-or-beat activity (p-value=0.081, one-tailed) for treatment firms relative to control firms, consistent with H4.

One immediate concern is whether the provision of cash flow forecasts is associated with a decline in economic performance, which could affect meet-or-beat tendencies. However, we observe increasing operating cash flows for treatment firms relative to control firms (p=0.034), which mitigates the concern that a deterioration in cash flows prompts analysts to begin providing cash flow forecasts. We do, however, observe a relative decrease in market-to-book (MTB) for treatment firms, but there is no relative change in Altman's *Z*. Moreover, we observe relative increases (decreases) in earnings growth (losses) for treatment firms. Thus, there does not appear to be deterioration in firm performance after the provision of cash flow forecasts for our treatment firms. Nevertheless, we control for firm performance in both our accrual tests and our meet-or-beat analysis reported below.

4.2. Results of accrual tests

The results of our accrual quality tests are reported in Table 2. Significance tests are one-sided where directional predictions are offered, and are two-sided otherwise. Panel A presents estimates of the changes in the average magnitude of positive, negative, and the absolute value of abnormal accruals moving from the pre-CF period to the post-CF period for our treatment and control samples. For this regression, we use firm-level abnormal accrual estimates averaged across years within the pre-CF period and within the post-CF period. This technique mitigates concerns about (a) residual autocorrelation in "difference-in-differences" designs using panel data (Bertrand et al., 2004), and (b) mechanical year-to-year reversals in accruals.

Recall that $\beta_2+\beta_3$ (β_2) measures the incremental change in abnormal accruals for the treatment (control) sample in the post-CF forecast period relative to the pre-CF forecast period. Therefore, β_3 is the incremental shift in abnormal accruals unique to treatment firms. We expect β_3 and $\beta_2+\beta_3$ to be negative for positive and absolute values of abnormal accruals, and positive for negative abnormal accruals for the treatment sample. For positive abnormal accruals, $\beta_2+\beta_3=-0.010$ and is significantly different from zero ($p<0.01$), which indicates that treatment firms experience a significant decline in income-increasing abnormal accruals after the provision of cash flow forecasts. β_2 is 0.009 ($p<0.10$), indicating that control firms exhibit a slight increase in upward accrual management in the post-CF period relative to the pre-CF period. The difference between treatment and control samples in these changes in positive abnormal accruals (β_3) is -0.019, which is significant at $p<0.01$. Thus, treatment firms exhibit an incremental greater decline in income-increasing abnormal accruals from pre- to post-CF periods relative to matched control firms.

We posit in Section 2.4 that the provision of cash flow forecasts may deter downward earnings management as well as upward earnings management. Panel A of Table 2 provides some weak evidence consistent with this conjecture. The average magnitude of income-decreasing abnormal accruals for treatment firms is smaller (i.e., less negative) after the issuance of cash flow forecasts relative to before the provision of cash flow forecasts as $\beta_2+\beta_3$=0.012, which is marginally significant at $p<0.10$. The temporal decline in the magnitude of negative abnormal accruals for control firms is smaller in magnitude (β_2=0.006), and this change is insignificantly different from zero. The difference in the changes in income-decreasing abnormal accruals across samples (β_3) is insignificant.

The last column of Panel A of Table 2 presents results for the absolute value of abnormal accruals. Consistent with our prediction, treatment firms experience a significant decline in absolute abnormal accruals after the provision of cash flow forecasts ($\beta_2+\beta_3=-0.011$, significant at $p<0.05$), while the decline for control firms (β_2) is insignificant. However, the difference across samples in shifts in the absolute value of abnormal accruals, β_3, is only weakly significant ($p<0.10$).[10] Overall, the results in Panel A of Table 2 provide evidence that the provision of cash flow forecasts deters income-increasing earnings management, while the evidence with respect to income-decreasing earnings management is weaker.

[10] This result is likely attributable to our abnormal accrual estimates being more precise in our treatment sample. In separate regressions within our treatment and control samples, the standard error for the *Post_CF* estimate in our control sample is more than 60% larger the standard error in our treatment sample. This is consistent with the increased accrual "noisiness" in our control firms that we document in Panel B of Table 2.

Table 2
Time-series changes in average abnormal accruals and earnings quality.

Panel A: Mean differences in abnormal accruals

$ABNACC_t=\alpha+\beta_1 TREAT_t+\beta_2 POST\_CF_t+\beta_3 POST\_CF_t{*}TREAT_t+\beta_4 ROA_t+\beta_5 ROA_t{*}TREAT_t+\varepsilon_t$ (2)

	Dependent variable: positive abnormal accruals			***Dependent variable: negative abnormal accruals***			***Dependent variable: abs. value of abnormal accruals***		
	Pred. sign	Estimate	*t*-stat	Pred. sign	Estimate	*t*-stat	Pred. sign	Estimate	*t*-stat
α Intercept	?	0.092***	23.45	?	−0.102****	−12.9	?	0.094****	18.51
β_1 Treat	?	−0.023***	−4.75	?	0.019*	1.91	?	−0.015**	−2.38
β_2 Post_CF	?	0.009*	1.70	?	0.006	0.58	?	0.002	0.21
β_3 Post_CF*Treat	–	−0.019***	−2.88	+	0.006	0.43	–	−0.013*	−1.50
β_4 ROA	?	−0.216***	−14.27	?	0.219***	8.40	?	−0.199***	−11.35
β_5 ROA*Treat	?	0.138***	6.74	?	0.197***	5.83	?	−0.079***	−3.46
Test: $\beta_2+\beta_3=0$	–	−0.010***	2.57	+	0.012*	1.50	–	−0.011**	2.30

Panel B: Mean differences in accrual quality

		Before first cash flow forecast	After first cash flow forecast	Diff.
s^2	Treatment	0.023	0.017	−0.006***
s^2	Control	0.028	0.031	0.003**

This table presents differences in: (1) average levels of positive, negative, and absolute abnormal accruals and (2) earnings quality, measured as the residual variance from a regression of accruals on temporally adjacent cash flows across our treatment and control samples. See Table 1 for details as to the construction of these samples. In Panel A, abnormal accruals are the residuals from the following regression (estimated by year and 2-digit SIC): $Accruals_t=\alpha+\beta_1\,((1+k)\Delta Sales_t-\Delta Receivables_t)+\beta_2\,PPE_t+\beta_3\,Accruals_{t-1}+\beta_4\,SalesGrowth_t+\varepsilon_t$ (see Dechow et al., 2003 for further estimation details). *Treat* is an indicator variable set to 1 if the observation belongs to the treatment sample, *Post_CF* is an indicator variable set to 1 if an observation belongs to the "post" period in either sample, and *ROA* is income before extraordinary items scaled by average total assets. We use average abnormal accrual measures by firm in the "pre" and "post" periods in the regression. In Panel B, accrual quality is the estimated residual variance (s^2) from the following regression: $Accruals_t=\alpha+\beta_1 CFO_{t-1}+\beta_2 CFO_t+\beta_3 CFO_{t+1}+\varepsilon_t$. The significance of the difference in s^2 across samples is tested using an *F*-test described in Appendix A. All tests are two-sided, where directional differences are predicted. See Appendix C for variable definitions and measurements.
*,**,*** Indicates significance at 10%, 5% and 1% levels.

Given the patterns above, one might be concerned that analysts specifically targeted treatment firms for cash flow forecast provision in response to more severe accrual manipulations by these firms. However, estimates of β_1 (the difference in abnormal accruals for treatment firms relative to control firms in the pre-CF period) in Panel A of Table 2 are not consistent with this conjecture. In fact, treatment firms appear to exhibit less accruals management in the pre-CF period, with smaller positive ($p<0.01$), smaller negative ($p<0.10$), and smaller absolute ($p<0.05$) abnormal accruals.

Panel B of Table 2 reports our second accrual quality test. Treatment firms exhibit significantly less accrual noise after the provision of cash flow forecasts compared to the pre-CF period (change in $s^2(\varepsilon)=-0.006$, significant at $p<0.01$) consistent with an increase in accrual quality. We do not observe a similar pattern for control firms. In fact, their accrual quality actually deteriorates over time (the change in $s^2(\varepsilon)=0.003$, which is significantly different from zero at $p<0.01$).

In summary, our accrual tests broadly support H1—our prediction that the provision of cash flow forecasts acts to deter earnings management through accrual manipulation. We observe significant declines in the magnitude of income-increasing and unsigned abnormal accruals, along with a decline in accrual noise after the provision of cash flow forecasts among our treatment firms. We do not observe similarly significant patterns among our control firms.

4.3. Results of real activities management and downward earnings guidance

Table 3 presents our tests of H2—the prediction that the use of real activities management to increase earnings is likely to increase after the provision of cash flow forecasts. Consistent with our prediction, in Panel A we observe evidence that average abnormal discretionary expenditures decline after the provision of cash flow forecasts among our treatment firms (*p*-value <0.01). We do not observe a significant decline for control firms, and the difference across the two samples is significant (*p*-value <0.05). For abnormal production, we do not observe a significant increase among our treatment or control firms. One explanation is that over-production increases inventory accruals, which is not a desirable outcome for a firm facing an implicit accrual forecast. Finally, we find a significant decline in average abnormal CFO among treatment firms after the provision of cash flow forecasts (*p*-value <0.01), but we also observe a significant decline for control firms as well (*p*-value <0.05). The difference is not significant across samples, so we are unable to conclude that the decrease in abnormal CFO is unique to treatment firms. Overall, the real activities tests in Panel A provide modest support for H2.

Table 4 provides evidence on downward expectations management. The variable of interest in Table 4 is the coefficient on *POST_CF*, which measures the change in the probability of expectations management from the pre-CF period to the post-CF period. H3 predicts that this coefficient will be positive for our treatment sample. Consistent with this prediction, we observe a significant increase in the probability of downward expectations management after the provision of cash flow forecasts

Table 3
Changes in real activities management after the issuance of cash flow forecasts.

	Treatment			Control		
	Pre	Post	Diff	Pre	Post	Diff
Abnormal discretionary expenditures (ABNDISC)						
Mean	−0.040	−0.075	−0.035***	0.076	0.068	−0.008
t-stat	−5.97	−15.06	−4.16	8.88	11.14	−0.73
	Treatment change − Control change			−0.027		
	t-stat			−2.13**		
Abnormal production (ABNPROD)						
Mean	−0.053	−0.05	0.003	−0.007	−0.002	0.005
t-stat	−11.69	−13.4	0.42	−1.38	−0.58	0.71
	Treatment change − Control change			−0.002		
	t-stat			−0.27		
Abnormal cash flows (ABNCFO)						
Mean	0.051	0.028	−0.023	0.069	0.051	−0.018
t-stat	9.45	6.03	−3.27***	10.84	11.29	−2.35**
Treatment change − Control change				−0.005		
t-stat				−0.58		

Estimates of real activity management are obtained as set forth in Roychowdury (2006). Abnormal discretionary expenditures are estimated as the residuals from a regression, by industry and year, of R&D, advertising, and SG&A on current sales. Abnormal production is estimated as the residual from a regression, by industry and year, of COGS plus the change in inventory on current sales and current and lagged changes in sales. Abnormal CFO is estimated as the residual from a regression, by industry and year, of COGS plus the change in inventory on current and lagged sales. All variables are scaled by lagged total assets. See Roychowdury (2006) for further estimation details.

Table 4
Changes in downward expectations management after the issuance of cash flow forecasts.

$$Prob(EXPMGMT_t=1)=\alpha+\beta_1\ POST\_CF_t+\beta_2\ SIZE_t+\beta_3\ MTB_t+\beta_4\ RD_t+\beta_5\ LOSS_t+\beta_6\ LITIGATION_t+\beta_7\ LABOR_t+\beta_8\ ISSUE_t+\beta_9\ RELEVANCE_t+\varepsilon_t \quad (8)$$

	Treatment			Control		
	Pred. Sign	Estimate	*t*-stat	Pred. Sign	Estimate	*t*-stat
Intercept	?	−0.636***	−4.24	?	−0.725***	3.73
Post_CF	+	0.099**	1.90	?	−0.036	0.54
Size	+	0.125***	6.82	+	0.167***	6.29
MTB	+	0.031***	3.98	+	0.041***	3.99
RD	+	−0.665**	−2.03	+	−0.956***	3.63
Loss	?	0.260***	3.61	?	0.419***	4.88
Litigation	+	−0.176***	−2.81	+	−0.220***	2.89
Labor	+	−0.009	−0.13	+	−0.127	1.49
Issue	+	0.215***	3.07	+	0.086	1.02
Relevance	+	−0.026**	−2.37	+	0.003	0.20
Test: $\beta_{1\text{treatment}}=\beta_{1\text{control}}$		0.135***	1.70			

Following Matsumoto (2002) we estimate the expected change in EPS by regressing EPS changes on cumulative stock returns and lagged EPS changes each year. We then add this expected change to prior year EPS to obtain the "expected" forecast of current EPS. If the most recent actual forecast of current EPS is less than this "expected" forecast, we consider expectations to have been managed downward. We create a binary variable, EXPMGMT, equal to 1 if expectations have been managed down and 0 otherwise. We then use a logistic regression to estimate the effect of cash flow forecasts on the probability that $EXPMGMT_t=1$. *Post_CF* is an indicator variable set to 1 if an observation belongs to the "post" period in either the treatment or control samples (see Table 1). We estimate a clustered logistic regression to allow for autocorrelation within firms over time. All significance levels are two-sided, except where directional differences are expected. See Appendix C for variable definitions and measurements.
*,**,*** Indicates significance at 10%, 5% and 1% levels.

for our treatment firms (p-value <0.05). We do not observe a similar increase for control firms, and the difference across samples is significant (p-value <0.05). Thus, the probability of downward expectations management increases among treatment firms after the provision of cash flow forecasts, consistent with H3.

Table 5
Cross-sectional relation between cuts in abnormal accruals and alternative benchmark beating mechanisms.

$$Prob(CUTACRR_t = 1) = \alpha + \beta_1\ ABNDISC_t + \beta_2\ ABNPROD_t + \beta_3\ ABNCFO + \beta_4\ EXPMGMT_t + \varepsilon_t \quad (9)$$

	Treatment			Control		
	Predicted Sign	Parameter	*t*-stat	Predicted Sign	Parameter	*t*-stat
Intercept		−0.588	8.14***		−0.594	−6.18***
ABNDISC	−	−1.010	−3.96***	?	−0.353	−0.97
ABNPROD	+	0.280	0.81	?	0.318	0.73
ABNCFO	−	1.170	3.31***	?	0.492	0.85
EXPMGMT	+	0.240	2.93***	?	0.096	1.13

CUTACCR is a dummy variable equal to 1 if a firm cut its average level of positive abnormal accruals from the pre to the post period (see Table 1). Abnormal discretionary expenditures (ABNDISC), production (ABNPROD), and cash flows (ABNCFO) are defined in Table 3 and Appendix C. The regression is estimated cross-sectionally among treatment and control firms in the post-CF period. Standard errors are clustered by firm.
*, **,*** Indicates significance at 10%, 5% and 1% levels.

4.4. Results linking changes in discretionary accruals to alternative benchmark beating mechanisms

In this section we examine more directly whether treatment firms tradeoff real activities management and downward earnings guidance for accruals management following the provision of cash flow forecasts. Table 5 provides estimates of the tradeoffs modeled in Eq. (9) for both treatment and control firms. Essentially, this cross-sectional "micro-analysis" tests whether firms that exhibit cuts in their average level of positive abnormal accruals from the pre- to post-CF period exhibit greater use of real transaction management or downward earnings guidance in the post-CF period relative to firms that do not. While we expect to observe such tradeoffs among treatment firms, we have no reason to expect tradeoffs for control firms.

The results indicate treatment firms that cut their positive abnormal accruals from the pre- to post-CF period have lower discretionary expenditures (p-value <0.01) and are more likely to have managed expectations downward (p-value <0.01). Not surprisingly given our results in Table 3, we find little effect for abnormal production. Interestingly, though, we find firms that cut their positive abnormal accruals actually have higher abnormal cash flows in the post-CF period (p-value <0.01), inconsistent with the findings in Table 3. Part of this effect could be driven by firms' attempts to manage cash flows after the provision of cash flow forecasts. Alternatively, this effect could be driven by choices to cut costs not classified as "discretionary" in nature.[11]

For control firms, we observe no significant tradeoffs among alternative benchmark beating mechanisms in the post-CF period. This findings makes sense given that control firms do not have cash flow forecasts in the post-CF period and, thus, do not face the same incentives to tradeoff accrual management for other forms of benchmark beating. In sum, the "micro-level" results in Table 5 provide evidence that treatment firms make tradeoffs between accrual management and alternative mechanisms to achieve earnings benchmarks in the post-CF period, but we find no evidence of this for control firms.

4.5. Benchmark beating results

Table 6 presents our test of H4 regarding changes in benchmark beating behavior. We use the logistic model in Eq. (10) to test whether there is an overall decrease in the probability of meeting or beating earnings forecasts after the provision of cash flow forecasts. We estimate separate regressions for our treatment and control samples.[12] For our treatment sample, the coefficient on the cash flow forecast dummy variable (*POST_CF*) is negative and significant ($p<0.01$), as predicted. Treatment firms exhibit a lower probability of meeting or beating analysts' earnings forecasts after the provision of cash flow forecasts. For our control sample, the coefficient on the *POST_CF* variable is insignificantly different from zero. A test of the equality of the β_1 coefficient across our treatment and control samples (reported at the bottom of Table 6) is rejected at $p<0.01$. Thus, firms with cash flow forecasts exhibit a significantly greater decline in the tendency to meet or beat analysts' earnings forecasts after the provision of cash flow forecasts as compared to the control firms without cash flow forecasts. The loadings on the control variables are generally consistent with expectations across samples, except that *CFO* and *ACC* are insignificant for our control sample. Further investigation (untabulated) reveals that our *LOSS* and *EARNGROW* variables completely absorb the explanatory power of cash flows and accruals (*ROA*) in predicting meet-or-beat activity (*MB*) for this sample.

To assess the economic significance of our findings, we calculate the marginal effect of the *POST_CF* variable, which is akin to a slope coefficient in a linear regression (Agresti, 2002, Chapter 5). We calculate the marginal effect as the change in the

[11] Still another, more mechanical, possibility looms large. There is a very strong negative relationship between accruals and cash flows at the firm level (Dechow, 1994; Sloan, 1996; Dechow and Dichev, 2002). Our results for the positive relation between declining abnormal accruals and higher abnormal cash flows could be driven by this effect.

[12] Due to the time-series nature of the data, we estimate a clustered logistic regression to allow the disturbances to be correlated within firms over time (Liang and Zeger, 1986). Results are inferentially similar if we estimate a standard logistic regression.

Table 6
Time-series effect of the issuance of cash flow forecasts on the probability of meeting or beating analysts' earnings forecasts.

$$Prob(MB_t=1)=\alpha+\beta_1 POST\_CF_t+\beta_2 CFO_t+\beta_3 ACC_t+\beta_4 CAPINT_t+\beta_5 ALTZ_t+\beta_6 CHOICE_t+\beta_7 SIZE_t+\beta_8 BLOAT_t+\beta_9 SHARES_t$$
$$+\beta_{10} MTB_t+\beta_{11} FOLLOW_t+\beta_{12} PMB_t+\beta_{13} REVDOWN_t+\beta_{14} WRITE_t+\beta_{15} LOSS_t+\beta_{16} EARNGROW_t+\varepsilon_t \quad (10)$$

Variables	Treatment sample			Control sample		
	Predicted Sign	Coefficient	*t*-stat	Predicted Sign	Coefficient	*t*-stat
Variable of interest						
Post_CF	–	−0.216***	−3.38	?	0.019	0.25
Control variables						
CFO	+	0.495**	2.06	+	−0.011	0.07
ACC	+	0.561**	2.18	+	−0.016	0.07
CAPINT	?	−0.039	−1.52	?	0.010	0.98
ALTZ	+	0.008**	1.86	+	0.003	0.67
CHOICE	?	−0.052	−0.27	?	−0.163	0.72
SIZE	+	0.051**	1.81	+	0.095***	2.62
BLOAT	–	−0.005	−0.28	–	0.018	1.64
SHARES	–	−0.001***	−3.07	–	0.000	0.58
MTB	+	0.003	0.43	+	0.010	1.05
FOLLOW	+	0.022***	5.02	+	0.012*	1.67
PMB	+	0.458***	8.41	+	0.919***	13.70
REVDOWN	?	0.096	1.61	?	0.002	0.04
WRITE	–	−0.127**	−2.16	–	0.019	0.26
LOSS	–	−0.218***	−2.52	–	−0.441***	4.47
EARNGROW	+	0.374****	5.87	+	0.605***	8.23
Test: $\beta_{1\text{treatment}}=\beta_{1\text{control}}$		−0.235***	2.56			
Industry & year dummies		Included			Included	

See Appendix C for variable definitions. The logit regression is estimated separately using our treatment and control samples (see Table 1 for sample construction). *Post_CF* is an indicator variable set to 1 if an observation comes from the post-CF forecast period in either sample, and zero otherwise. To avoid inflated test statistics due to potential autocorrelation in the data, we estimate a logistic regression with clustered standard errors. Results are similar if we use a standard logistic regression instead. All significance levels are based on one-tailed probabilities if a directional prediction is offered, and are based on two-tailed probabilities otherwise.

*,**,*** Indicates significance at 10%, 5% and 1% levels.

probability that MB=1 given a change in the *POST_CF* variable from 0 to 1, holding all other variables constant at their mean values. In untabulated analysis, we find the marginal effect of *POST_CF* is roughly −0.05, which implies that firms face a probability of meeting earnings expectations that is 5 percentage points lower after the issuance of cash flow forecasts. Overall, our benchmark-beating tests support H4.

Our interpretation of the meet-or-beat results is based on the maintained hypothesis that analysts do not purposely change their behavior with respect to forecasting earnings in the post-CF period relative to the pre-CF period. If analysts are aware that the provision of cash flow forecasts make it more costly for managers to manage earnings upward through accruals, they may *lower* their earnings estimates relative to what they might otherwise be to compensate for this fact. But such adjustments should result in no change in the incidence of meet-or-beat behavior, or possibly an increased incidence of meet-or-beat behavior if firms are able to compensate for the loss of flexibility in managing accruals through real transactions management. This prediction, however, runs counter to what we observe. Moreover, Call et al. (2009) find that analysts' earnings forecasts are more accurate when they issue cash flow forecasts relative to when they do not. Thus, their finding suggests there is no systematic attempt by analysts to bias their earnings forecasts up or down following the provision of cash flow forecasts.

To further establish that our meet-or-beat results are due to changes in firm behavior rather than changes in analysts' forecasting behavior, we conduct a "micro-level" analysis for our meet-or-beat tests, similar to the tests reported in Table 5 on whether firms tradeoff accruals management for alternative benchmark-beating mechanisms. In Table 7 we estimate a logit regression with MB as the dependent variable and the level of various benchmark-beating mechanisms after the provision of cash flow forecasts as explanatory variables. These mechanisms include abnormal accruals, our real activities management estimates, and our indicator for downward expectations management. Our goal is to test the conjecture that firms that use these mechanisms increase their likelihood of beating earnings targets after the provision of cash flow forecasts. In general, the evidence in Table 7 supports this conjecture. Firms with higher abnormal accruals, lower discretionary expenditures, and those that manage expectations downward are more likely to meet earnings targets. As in Tables 3 and 5 we find no results for abnormal production. Similar to Table 5, there is a positive relationship between abnormal cash flow and MB (p-value <0.01), inconsistent with the use of channel stuffing or excessive discounts to meet earnings targets. However, this relation is consistent with the simple notion that higher cash flow often results in higher earnings, and thus a higher probability of meeting EPS targets.

Table 7
Effects of alternative benchmark beating mechanisms on meet-or-beat probability.

$Prob(MB_t=1)=\alpha+\beta_1\ ABNACC_t+\beta_2\ ABNDISC_t+\beta_3\ ABNPROD_t+\beta_4\ ABNCFO_t+\beta_5\ EXPMGMT_t+\varepsilon_t$

	Predicted Sign	Parameter	t-stat
Intercept		0.538	7.58***
ABNACC	+	0.781	1.71**
ABNDISC	–	−0.995	−3.73***
ABNPROD	?	−0.066	0.17
ABNCFO	+	1.166	3.12***
EXPMGMT	+	0.175	2.09**

EXPMGMT is defined in Appendix C. All other variables are defined in Table 3. The regression is estimated among treatment firms in the post period (after the issuance of cash flow forecasts). Standard errors are clustered by firm.
*,**,*** Indicates significance at 10%, 5% and 1% levels.

In summary, our empirical tests broadly support H1 through H4. At the "macro" level, we observe an increase in accrual quality and a significant decline in positive abnormal accruals after the issuance of cash flow forecasts. We also observe accompanying cuts in discretionary expenditures and an increase in the use of downward expectations management. We find weaker of evidence of increased channel stuffing and excessive discounts, and no evidence of increased abnormal production. Finally, we show that the probability of meeting or beating earnings targets declines, on average, after the provision of cash flow forecasts. At the "micro" level, we find evidence that firms that cut their income-increasing abnormal accruals after the issuance of cash flow forecasts have lower discretionary expenditures and a higher incidence of downward expectations management, and that use of these alternative mechanisms increases meet-or-beat probabilities at the firm level.

5. Alternative explanations

One competing explanation for our benchmark beating results is that the issuance of cash flow forecasts by analysts portends deterioration in a firm's performance in the future. That is, as market participants become concerned about a firm's viability or solvency, they demand forecasts of operating cash flow. As a result, the patterns we observe related to meeting earnings expectations may simply be a manifestation of economic decline. However, the descriptive statistics in Table 1 indicate steady to slightly increasing cash flows and an increasing incidence of earnings growth after the provision of cash flows for treatment firms, which is inconsistent with a widespread deterioration in financial performance. In addition, we include a variety of performance-related variables in our tests. We use performance-adjusted abnormal accruals in our accrual tests and we control for ROA (CFO+accruals), Altman's *Z*, asset write-offs, losses, earnings growth, and analysts' downward forecast revisions in our meet-or-beat tests.

Another competing explanation for our findings is that once analysts start forecasting operating cash flow, meeting earnings targets becomes less important while meeting cash flow targets becomes more important, and firms face a tradeoff between the two. We investigate this possibility in Table 8. Panel A presents a 2×2 contingency table that contains the incidence of meeting or beating cash flow and earnings forecasts in the post-CF period. Earnings and forecast data are obtained from I/B/E/S. If the actual value of cash flows is missing in I/B/E/S, we use actual operating cash flow per COMPUSTAT, adjusted for extraordinary items and stated on a per-share basis. Panel A reveals two interesting patterns. First, firms are most likely to beat both forecasts, followed by cases where firms meet earnings targets but miss cash flow targets. Cases where firms meet cash flow targets but miss earnings targets are the most rare in our sample (16% of observations). Second, inconsistent with the idea of a tradeoff, inspection of the rows and columns indicates a positive relation between meeting both forecasts. For example, the probability of beating the earnings target conditional on beating the cash flow target is 0.70 [0.374/(0.374+0.160)], while this probability falls to 0.62 conditional on missing the cash flow target [0.29/(0.29+0.175)]. A chi-square test rejects independence between the two benchmarks (p-value <0.01).

In Panel B of Table 8, we test tradeoff effects directly. We estimate the full logit model in Table 6 among treatment firms after the provision of cash flow forecasts, except we insert a dummy variable equal to one if a firm meets or beats its cash flow target. To save space, we do not table results for control variables, but we note they are quite similar to those in Table 6. Panel B of Table 8 indicates a positive relationship between meeting cash flow targets and meeting earnings targets (p-value <0.01). This is not too surprising, given that many actions that boost cash flows (e.g., cutting expenses or increasing sales) also boost income.

Finally, in Panel C of Table 8 we conduct the most direct test of the conjecture that firms' focus on meeting cash flow forecasts at the expense of meeting earnings forecasts as a competing explanation for our results. We use our treatment sample to measure a firm's average value for the meet-or-beat (MB) variable in the pre-CF and post-CF periods and classify firms into two groups: those with a decreased tendency and those with an equal or increased tendency to meet EPS targets in the post-CF period. We then measure the difference in their tendency to meet cash flow targets in the post-CF period. If a focus on cash flow targets explains why some firms begin to miss EPS targets in the post period, we expect these firms to exhibit a greater propensity to meet cash flow targets. We find just the opposite. Firms with a decreased tendency to meet earnings

Table 8
Tradeoffs between meeting cash flow forecasts and earnings forecasts.

Panel A: Incidence of meeting or missing cash flow and earnings forecasts

		Earnings forecast		
		MB	Miss	Total
Cash flow forecast	MB	0.374	0.160	0.534
	Miss	0.290	0.175	0.466
	Total	0.664	0.336	
	χ^2 stat	21.62***		

Panel B: Association between meeting earnings forecasts and cash flow forecasts after first cash flow forecast
$Prob(MB=1)=\alpha+\beta_1(CashBeat)+\beta' Controls+\varepsilon$

	Treatment		
	Pred. Sign	Estimate	*t*-stat
Intercept	?	−0.758	0.13
CashBeat	?	0.294***	3.55

Panel C: Association between meeting cash flow targets and the change in tendency to meet EPS forecasts (MB) after first cash flow forecast

	% of observations where firm met cash flow forecast	*N*
Firms with decreased tendency to MB	0.4949	1184
Firms with equal or increased tendency to MB	0.5415	2347
Diff	0.05	
p-Value	< 0.01	

Panel A presents a 2×2 contingency table for missing or meeting/beating earnings and cash flow forecasts among treatment firms in the post period (see Table 1). Earnings and forecast data are obtained from I/B/E/S. If the actual value of cash flows is missing in I/B/E/S, we use actual operating cash flow per COMPUSTAT, adjusted for extraordinary items and stated on a per-share basis. In Panel B, we estimate the logit regression from Table 5 among treatment firms in the post period, except we insert a dummy variable equal to 1 if the firm met or exceeded its cash flow target. Loadings on control variables are not tabled to save space. In Panel C, we measure a treatment firm's average value for the earnings meet-or-beat variable in the "pre" and "post" samples and classify firms into two groups: those with a decreased tendency and those with an equal or increased tendency to meet or beat. We then examine their incidence of meeting or beating cash flow targets.

targets exhibit a *lower* tendency to meet cash flow targets ($p<0.05$) after the provision of CF forecasts. Overall, we find no evidence to suggest our results are driven by managers shifting their focus to meeting or beating cash flow targets at the expense of earnings targets.

6. Conclusion and directions for future research

When analysts forecast both operating cash flow and earnings, they also implicitly provide a forecast of operating accruals. Thus, cash flow forecasts enable investors and regulators to decompose an earnings surprise into the portion attributable to cash flow and the portion attributable to accruals. We posit that cash flow forecasts make accrual manipulations to manage earnings more transparent, which increases the expected costs to firms and managers of engaging in opportunistic earnings management through accrual manipulations. Accordingly, we predict that the provision of cash flow forecasts deters firms from engaging in accrual manipulation to manage earnings. As a consequence, we predict that accrual quality will improve and firms' propensity to meet or beat earnings benchmarks will decline following the provision of cash flow forecasts.

Overall, the evidence broadly supports our predictions. Using inter-temporal change analysis, we find that accrual quality improves, and the probability of meeting earnings targets declines, after analysts begin issuing cash flow forecasts. Tests using a propensity-score matched control sample do not reveal similarly significant changes in accrual quality or benchmark beating. Additional analyses reveal that firms for which cash flow forecasts are provided turn to other benchmark-beating mechanisms, such as real activities management and earnings guidance, following the provision of cash flow forecasts. Our findings are of potential interest to investors and regulators because we identify a relatively low cost, market-driven mechanism that helps curb firms' attempts to manipulate accruals to meet analysts' earnings estimates.

Our conclusions are subject to standard caveats regarding endogeneity. While our propensity-score matching procedure and difference-in-differences design help mitigate such concerns, there is still a possibility that our findings are driven by some omitted variable(s). We believe, however, that this possibility is remote given our findings that treatment firms seem to trade off accrual management for real activities management and downward earnings guidance—actions that would be expected if accrual manipulation is constrained (i.e., becomes more costly).

We offer several avenues for further research. First, the present study investigates the role of cash flow forecasts as a deterrent to avoiding negative earnings surprises. Future research could examine whether cash flow forecasts deter attempts by firms to avoid earnings declines or losses—two other thresholds that have been examined in the literature. Second, examining whether other multiple analyst forecasts (e.g., earnings and revenues) constrain earnings management in other ways is an interesting area for future research. For example, does analyst provision of both sales and earnings forecasts deter firms from attempting to manage earnings through revenues (e.g., engaging in channel stuffing)? Third, we do not contend that all firms will be deterred from benchmark-beating by cash flow forecasts. Some firms may substitute other mechanisms for avoiding negative earnings surprises, such as guiding analysts' earnings forecasts or manipulating real activities (see Section 4.4). Presumably, the cost and effectiveness of these other mechanisms vary cross-sectionally, and one might conjecture these differences help explain why some firms are more likely to meet analysts' earnings forecasts in the presence of cash flow forecasts than other firms. Future research could test the validity of this conjecture. Finally, cash flow forecasts allow investors to more easily measure "unexpected accruals." Another fruitful area of research would be to examine the degree to which "unexpected accruals" based on analysts' cash flow and earnings forecasts correspond to measures of "abnormal accruals" from extant Jones-based models.

Appendix A. Overview of propensity score matching procedure

DeFond and Hung (2003) identify six determinants of analyst cash flow forecast provision: (1) magnitude of accruals (ACC), (2) earnings volatility (VOL), (3) accounting choice heterogeneity (CHOICE), (4) Altman's *Z*-score (ALTZ), (5) capital intensity (CAPINT), and (6) market value of equity (SIZE). They argue investors have a greater demand for cash flow information when accruals are large, when earnings are volatile, when the firm is distressed, and when a firm's accounting choices (e.g., LIFO/FIFO) differ from the industry norm. In addition, firms with high capital intensity require large operating cash flows to fund maintenance and capital investment, creating demand for cash flow projections. Finally, larger firms face more capital market scrutiny, creating a demand for additional financial information like operating cash flow forecasts.

We use a propensity-score matching procedure (Rosenbaum, 2002; Rosenbaum and Rubin, 1983) to select our control sample. For each initial year of cash flow forecast provision for our treatment firms (i.e., those with cash flow forecasts), we select a matching firm without a cash flow forecast from the same year that has the closest "propensity score." This propensity score is the predicted probability of a cash flow forecast from the following logit model proposed by Defond and Hung (2003):

$$
\begin{aligned}
&Prob(Cash\ Flow\ Forecast = 1) = \alpha + \beta_1 Accruals + \beta_2 Earnings\ Volatility + \beta_3 Accounting\ Choice \\
&\quad + \beta_4 Altman Z + \beta_5 Capital\ Intensity + \beta_6 MVE + \varepsilon
\end{aligned}
$$

We estimate the logit model on a pooled basis across all firms in the COMPUSTAT/IBES universe with available data from 1993 to 2004. See DeFond and Hung (2003) for detailed variable definitions. We make one slight modification to the specification in DeFond and Hung (2003). We use the signed value of accruals instead of the absolute value because, despite our matching procedure, we still want to control for differences in performance in many of our tests. Using the unsigned value of accruals makes the most sense from this perspective. Estimates from the model are shown in Table A1.

All determinants are significant and are of the proper sign. The mean values of the determinants variables and propensity scores for treatment and control firms in the matching year are given in Table A2.

Appendix B. Testing the equality of residual variance across regression equations

We are interested in whether the residual variance, σ^2, is different across two regression equations, which we label regressions 1 and 2 for convenience. There are K covariates and the sample sizes are N_1 and N_2. We calculate a test statistic, t, equal to the ratio of the two sample residual variance estimates (i.e., $t = s_1/s_2$, where $s_i = (1/N_i - k) * e_i' e_i$). This is simply a Goldfeld-Quandt (1965) statistic, though we are testing heteroskedasticity across (not within) regression equations. Under the null hypothesis, $\sigma_1^2 = \sigma_2^2 = \sigma^2$, $t \sim {}^{a}F(N_1 - k, N_2 - k)$.

Table A1

		Estimate	*t*-stat	*p*-value
Intercept		−7.454	−83.31	< 0.01
Accruals	ACC	0.838	11.52	< 0.01
Earnings Volatility	VOL	0.019	8.91	< 0.01
Accounting Choice	CHOICE	1.267	11.00	< 0.01
Altman's *Z*	ALTZ	−0.057	−19.51	< 0.01
Capital intensity	CAPINT	0.323	33.67	< 0.01
MVE	SIZE	0.939	74.55	< 0.01
Psuedo *R*-square		0.44		

To see why, note that if the disturbances are independent and normally distributed, then $(N_i-k)*(s_i/\sigma_i^2) \sim \chi^2(N_i-k)$. See DeGroot and Schervish (2002, Section 7.3) for a proof of this result. If the disturbances are not normally distributed, then $(N_i-k)*(s_i/\sigma_i^2) \sim {}^a\chi^2(N_i-k)$ as N_i gets large due to the central limit theorem. The test statistic t represents the ratio of two

Table A2

	Treatment	Control	Diff.
ACC	−0.078	−0.066	−0.012***
VOL	3.185	3.314	−0.129
CHOICE	0.145	0.142	0.003
ALTZ	4.393	3.714	0.679***
CAPINT	1.105	1.092	0.013
SIZE	6.841	6.501	0.340
Propensity Score	0.279	0.280	−0.001

*** Indicates significance at $p < 0.01$.

Table C1

Abnormal Accruals	ABNACC	From forward-looking, modified Jones model. See Dechow et al. (2003) for estimation details.
Abnormal Cash Flows	ABNCFO	See Roychowdury (2006) for estimation details.
Abnormal Discretionary Expenditures	ABNDISC	See Roychowdury (2006) for estimation details.
Abnormal Production	ABNPROD	See Roychowdury (2006) for estimation details.
Absolute Abnormal Accruals	ABSABNACC	Absolute value of abnormal accruals.
Total Accruals	ACC	Total accruals (data123-data308+data124) per COMPUSTAT divided by lagged total assets (data6)
Altman's *Z*-score	ALTZ	Following Altman (1968), the *Z*-score equals 1.2(Net working capital [data4–data5]/Total assets [data6])+1.4(Retained earnings [data36] /Total assets)+3.3(Earnings before interest and taxes [data178]/ Total assets)+0.6(Market value of equity [data25*data199]/Book value of liabilities [data181])+1.0(Sales[data12]/Total assets). All data is from COMPUSTAT.
Net Asset Bloat	BLOAT	Following Barton and Simko (2002) bloat is the lagged value of book equity (data216) per COMPUSTAT plus debt (data9 and data34), minus cash (data1), scaled by sales.
Capital Intensity	CAPINT	Gross PP&E (data7) divided by total net sales (data12) per COMPUSTAT
Cash Flow From Operations	CFO	Cash flow from continuing operations per COMPUSTAT (data308–data124), scaled by lagged total assets (data6)
Accounting Choice Heterogeneity	CHOICE	An index from 0 to 1 that captures the extent to which a firm's accounting choices in certain areas differ from the industry norm. For details of this variable definition, please see DeFond and Hung (2003).
Cumulative Return	CUMRET	12 month buy and hold, market adjusted return from month after last year's earnings annual announcement to month before current annual earnings announcement
Cut Accruals	CUTACCR	Equal to 1 if a treatment firms reduces it average level of positive ABNACC in the POST-CF period.
Earnings Growth	EARNGROW	Dummy variable set to 1 if change in income (data123) in COMPUSTAT is positive and 0 otherwise
Expectations Management	EXPMGMT	Indicator variable equal to 1 if the last forecast of EPS before the annual earnings announcement is less than the expected amount, where the latter is estimated from the model used in Matsumoto (2002).
Analyst Following	FOLLOW	# of individual analysts per the I/B/E/S detail file issuing EPS forecasts for the firm-year in question
Equity Issuance	ISSUE	Dummy variable equal to 1 if the firm issued equity (data108) per COMPUSTAT during the year and zero otherwise.
Labor Intensity	LABOR	Equal to 1 minus capital intensity
Litigation Risk	LITIGATION	Dummy variable equal to 1 if a firm is in industries prone to litigation as identified by Matsumoto (2002).
Loss Incidence	LOSS	Dummy variable set to 1 if income (data123) in COMPUSTAT is negative and 0 otherwise
Meet or Beat	MB	1 if the observation is on the "meet" side of the earnings surprise distribution and 0 otherwise. Earnings surprises are measured as the difference between reported EPS per I/B/E/S and the last available forecast in I/B/E/S prior to the earnings announcement.
Market-to-Book	MTB	Market value of equity (as defined above) divided by book value of equity per COMPUSTAT (data216).
Prior Meet or Beat	PMB	1 if the firm-year in question reported a positive earnings surprise in the previous year and 0 otherwise
Post Cash Flow Forecast	POST_CF	Equal to 1 if an observation is in or after the first year of cash flow forecast prevision. For control firms, this variable is measured in reference to the matching treatment firm.
R&D Intensity	RD	R&D expense (data46) per COMPUSTAT scaled by lagged total assets
Value Relevance of Earnings	RELEVANCE	Annual decile rank of the *r*-square from industry-year regressions of returns on earnings. See Matsumoto (2002) for further estimation details.
Downward Revision	REVDOWN	1 if the last available forecast of current-year EPS per I/B/E/S was less than the first forecast of current-year EPS and 0 otherwise.
Return on Assets	ROA	Income before extraordinary items (data123) per COMPUSTAT divided by lagged assets (data6).
# of Shares O/S	SHARES	# of shares used to calculate EPS (data54) in COMPUSTAT
Size	SIZE	log(Market value of equity [data25*data199])
Earnings Volatility	VOL	Coefficient of variation of earnings over the sample period.
Treatment	TREAT	Equal to 1 if a firm has a cash flow forecast and 0 otherwise.
Asset Writeoffs	WRITE	Following Elliot and Hanna (1996), this is a dummy variable set to 1 if special items (data17) in COMPUSTAT is negative and 0 otherwise.
Change in EPS	ΔEPS	Change in earnings per share per I/B/E/S scaled by lagged stock price from CRSP.

independent, (asymptotically distributed) chi-squared random variables, each divided by their degrees of freedom. Under the null hypothesis, the σ^2 terms cancel out, and t is distributed asymptotically F by the definition of the F distribution. Sufficient deviation in t from 1 leads to rejection of the null hypothesis.

A critical assumption in the preceding analysis involves independence in the residuals. The sample residual variances reported in the paper are based on OLS estimation, which assumes the theoretical residuals are uncorrelated. Since our regressions include multiple observations for the same firms over time, this assumption may be violated. If the residuals are serially correlated, then the distributional properties of our test statistic derived above may not hold. We attempt to mitigate this concern as follows. We allow residuals within (but not across) firms to be correlated over time and use generalized least squares (GLS) to incorporate this covariance structure into the parameter estimates in Eq. (3). GLS essentially transforms the theoretical disturbance vector to remove the hypothesized correlation between residuals. We then use the GLS-based residuals to construct our test statistic t.

Inferences using the GLS-based residuals are identical to those reported in the paper.

Appendix C. Variable definitions

See Table C1.

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