**Do analysts' cash flow forecasts improve the accuracy of their target prices?**[*]

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## Abstract

Current evidence on the sophistication of analysts' cash flow forecasts is ambiguous. For example, Call et al. (2009) show that issuing cash flow forecasts has important benefits for analysts' earnings forecasts, while Givoly et al. (2009) question the validity of this result, arguing that analysts' cash flow forecasts are simple extrapolations of their earnings forecasts and provide limited incremental information. More recently, Mohanram (2014) and Radhakrishnan and Wu (2014) show that the increasing incidence of cash flow forecasts has helped mitigate accruals mispricing. We contribute to the debate on the usefulness of analysts' cash flow forecasts and their effect on capital market outcomes by examining whether cash flow forecasts have incremental benefits over earnings for analysts' valuation outcomes. We find that analysts who are better at forecasting cash flows are better at forecasting target prices, even after controlling for the quality of their earnings forecasts. Our study provides confirmatory evidence on the sophistication of analysts' cash flow forecasts.



**Keywords:** Analysts, Cash flow forecasts, Target price accuracy, Valuation.

**JEL Classification:** M41, G12, G24, G29, C35

## 1. Introduction

Prior literature shows that issuing cash flow forecasts has important benefits for analysts' earnings forecasts. Call et al. (2009) find that earnings forecasts are more accurate when analysts also issue cash flow forecasts. They argue that when analysts accompany earnings forecasts with cash flow forecasts, they develop a better understanding of the time-series earnings process as a result of adopting a structured approach to forecasting a complete set of financial statements. Call et al. (2009) conclude that this should and does result in higher-quality earnings forecasts. The literature, however, also questions the usefulness and sophistication of analysts' cash flow forecasts. For example, Givoly et al. (2009) cast doubt on Call et al.'s (2009) results and find that, relative to earnings forecasts, analysts revise cash flow forecasts less frequently and cash flow forecasts are less accurate.

More recently, supporting the view that analysts' cash flow forecasts improve capital market outcomes, Mohanram (2014) and Radhakrishnan and Wu (2014) show that the increasing incidence of cash flow forecasts has helped mitigate accruals mispricing. Their results suggest that analysts' cash flow forecasts enable investors to price a firm more accurately and imply a direct link between analysts' cash flow forecasts and stock prices.

Our study contributes to the debate on the usefulness of cash flow forecasts and their effect on capital market outcomes by examining whether disclosing cash flow forecasts improves an analyst's target price accuracy. There are two reasons for examining this link. The first stems from Mohanram's (2014) finding of a negative relation between accruals and future returns when analysts provide cash flow forecasts. This suggests that when analysts provide forecasts of future accruals through their cash flow forecasts, this ameliorates accruals mispricing, and contributes to the argument that analysts who make cash flow forecasts provide useful signals to investors.

Mohanram's study helps to answer the question that Lehavy (2009) poses in relation to Call et al. (2009), namely: Why, given the benefits, do some analysts decide not to issue cash flow forecasts? Building on Mohanram (2014), we argue that analysts who issue cash flow forecasts possess better information, which their valuations should reflect, and we hypothesize that target price accuracy improves when analysts supplement their target prices with cash flow forecasts.

Second, while the literature shows that analysts generally favor earnings-based valuation (Govindarajan, 1980; Bradshaw, 2002; Demirakos et al., 2004; Asquith et al., 2005), the superiority of earnings over cash flow forecasts in analysts' valuations is not absolute. Demirakos et al. (2010) show that analysts make sophisticated valuation model choices and find that they are more likely to use the discounted cash flow (DCF) model than the price–earnings (PE) model when valuing more challenging firms. They conclude that analysts use DCF models more frequently than PE models when firm characteristics can bias earnings-based valuations. DeFond and Hung (2003) also find that analysts are more likely to provide cash flow forecasts in industries where earnings forecasts are less informative for valuation.[1] We build on this to argue that if analysts forecast cash flows when there is greater uncertainty about reported earnings, we expect them to incorporate cash flow information into their valuations. We examine whether cash flow forecasts have relevance for analysts' own target price valuations. This examination should be of interest to investors and provides further evidence on the sophistication of analyst cash flow forecasts. Our second hypothesis is that analysts' target price accuracy increases with the quality of their cash flow forecasts and our third hypothesis is that the improvement in the accuracy of target prices that comes from accompanying them with cash flow forecasts is greater for firms that are more challenging to value.

[1] For example, oil and gas analysts rely primarily on operating cash flows when comparing firm performance because they consider earnings unreliable due to differences in the reported earnings of these firms.

Using propensity score matching (PSM), we analyze the performance of analyst target prices accompanied by cash flow forecasts during the period 2000–2010. Our analysis shows that an analyst's target price accuracy improves when the analyst accompanies the target price with a cash flow forecast and the accuracy of the target price is higher when the accuracy of the cash flow forecast is higher. Our results suggest that analysts who are better at forecasting cash flows are also better at forecasting target prices. We also find that the increased accuracy of target prices accompanied by cash flow forecasts is greater for challenging-to-value firms than non-challenging firms and that the increased target price accuracy due to the increase in cash flow forecast accuracy is higher for firms that are more challenging to value. This points to the value and sophistication of analysts' cash flow forecasts.

Our results have important implications for research on the usefulness of cash flow forecasts, as they suggest that these forecasts are useful for analyst valuations. The results also extend our knowledge by offering insights into the 'black box' of analyst valuation. Studying the effect of cash flow forecasts on target prices is potentially more relevant for the debate on the usefulness of cash flow forecasts than is studying their effect on other analysts' research outputs (such as earnings forecasts). Prior evidence (e.g., Mohanram 2014) shows that stock prices reflect the relevance of cash flow forecasts for the capital market. Unlike earnings forecasts, analyst target prices are directly comparable to market prices. Target prices also provide a direct estimate of analysts' expectations of future stock returns, which earnings forecasts do not. Finally, measuring the accuracy of analysts' earnings forecasts requires a comparison with reported earnings, which are subject to earnings management. Measuring the accuracy of target prices, in contrast, requires a comparison with market prices, which are less subject to management influence.

An important caveat to our analysis is the assumption that analysts who do not issue cash flow forecasts either do not generate cash flow forecasts or at least do not undertake a rigorous, structural articulation of the financial statements to the same extent as analysts who issue cash flow forecasts. While we cannot observe what analysts choose not to publicly disclose, we believe that if analysts generate cash flow forecasts there is little cost to making them available and little incentive to withhold them.

Our results are relevant for users of sell-side analyst research, academics, investors, and companies. We expect our findings to improve our understanding of the value and sophistication of cash flow forecasts. Additionally, our findings shed light on the determinants of analyst target price accuracy and add to our understanding of the properties of target prices.

The paper continues as follows. Section 2 discusses related literature and develops our research hypotheses. We describe our sample and data in section 3 and research design in section 4. In section 5, we present sample descriptive statistics, empirical results, and additional analysis. Section 6 concludes.

## 2. Prior literature and research hypotheses

Financial analysts play a key role in capital markets, and their role has become of increasing interest to regulators and academics. Analysts have begun including cash flow forecasts in their equity reports relatively recently and their increasing availability has attracted the attention of academic research.[2] Early research investigated the determinants of investors' demand for cash flow forecasts (DeFond and Hung 2003). Later research has examined the effect of cash flow forecasts on managers' earnings reporting (McInnis and Collins 2011), cash flow forecast

[2] The frequency of cash flow forecasts accompanying earnings forecasts on I/B/E/S increased from 1 percent in 1993 to 15 percent in 1999 (DeFond and Hung 2003), to 32 percent in 2005 (Call et al. 2009), and to almost 50% by 2010 (Mohanram 2014).

availability and analyst earnings forecasts accuracy (Call et al. 2009), the market reaction to firms meeting or beating analysts' cash flow forecasts (Brown et al. 2013), and the determinants of cash flow forecast accuracy (Pae and Yoon 2012).

Despite the considerable attention paid to analyst cash flow forecasts in the recent literature, however, the debate on the sophistication of analyst cash flow forecasts remains unsettled. Mangen (2013) observes that this research area is still in its infancy. Recent evidence of Call et al. (2013) investigates the accruals adjustments that analysts make in order to forecast cash flows. They show that analysts incorporate meaningful estimates of working capital and other accruals to reconcile earnings and cash flow forecasts. Further, they find a significant market reaction to cash flow forecast revisions incremental to the reaction to earnings forecast revisions. This is consistent with Call et al.'s (2009) finding that disclosing cash flow forecasts improves the accuracy of analysts' earnings forecasts, suggesting that cash flow forecasts are sophisticated and are of value to investors. It is also consistent with earlier literature suggesting that analysts' decision to issue cash flow forecasts is not random and does not follow a simple time trend. DeFond and Hung (2003) study the determinants of the selective supply of cash flow forecasts and attribute this to investor demand. They find that the decision to issue cash flow forecasts depends on firm-specific factors, primarily proxies for uncertainty facing a firm, heterogeneous accounting choices, and financial distress. They show that the demand for cash flow forecasts increases when information on earnings alone is insufficient to assess firm value.

Supporting the view that analysts' cash flow forecasts improve capital market outcomes, Mohanram's (2014) finds that the increasing incidence of analyst cash flow forecasts is responsible for the recent decline in the accruals anomaly. When analysts forecast cash flows, they provide implicit forecasts of future accruals. Mohanram argues that if the accruals anomaly results from accruals mispricing, then the presence of information on expected future accruals, in the form of analyst cash flow forecasts, helps reduce the mispricing. Radhakrishnan and Wu (2014) provide support for these findings.

In contrast, Givoly et al. (2009) argue that cash flow forecasts are naïve extensions of earnings forecasts and question their usefulness given their low accuracy compared with earnings forecasts. Lehavy (2009) highlights robustness concerns in support of the view that cash flow forecasts are unsophisticated and questions the response-to-investor-demand explanation of DeFond and Hung (2003). Givoly et al. (2013) further challenge the sophistication of cash flow forecasts by arguing that Call et al.'s (2013) evidence is based on inappropriate benchmarks and tests of the sophistication of analyst cash flows. They note, however, that their findings that analyst cash flow forecasts are unsophisticated do not imply that analysts lack the necessary expertise and knowledge to perform their job, rather that accurately forecasting the components necessary to reconcile earnings to cash flows is a difficult task.

The literature as it stands needs further analysis to settle the debate on the sophistication of analyst cash flow forecasts. We contribute to this debate by arguing, based on evidence in Call et al. (2009, 2013), Mohanram (2014) and others, that analysts who provide cash flow forecasts possess better information and these forecasts contain information that is incremental to the information in earnings forecasts. Analyst valuations, in the form of target prices, should reflect this incremental information after controlling for the information content of earnings forecasts.

While research shows that reported cash flows and accounting earnings are each incrementally useful in assessing firm value (e.g., Bowen et al. 1987; Ali 1994; Dechow 1994), no prior study examines how analysts' cash flow forecasts affect their valuations. It is difficult to observe analyst valuation decision processes directly, but we can test whether issuing cash flow forecasts affects the quality of analysts' valuations. If we find evidence that analysts who make cash flow forecasts produce more accurate target prices, after controlling for the quality of their earnings forecasts, then this provides evidence supporting the sophistication of their cash flow forecasts.

In a recent attempt to penetrate the black-box of sell-side analysts, Brown et al. (2014) survey 365 analysts and conduct 18 follow-up interviews covering various topics, one of which is the inputs to analysts' earnings forecasts and stock recommendations. They find that most analysts rely on earnings-based valuations to support their stock recommendations.[3] Their survey also shows that most analysts state that they frequently use cash flow models to support their stock recommendations while they use other models much less frequently. This implies that cash flow forecasts along with earnings forecasts are a key factor in analyst valuation models. Additionally, Brown et al. (2014) find that analysts state that their primary motivation to issue accurate earnings forecasts is to use them as inputs to their valuations. They do not, however, survey analysts about their motivations for issuing cash flow forecasts. We argue that analysts who make cash flow forecasts use them as inputs to their valuations, either directly or indirectly.

We examine the effect of analysts' cash flow forecasts on their target price accuracy. We hypothesize that an analyst's target price accuracy is higher if the analyst also provides a cash flow forecast because analysts who make cash flow forecasts possess better information. This builds on Call et al.'s (2009) finding that the presence of cash flow forecasts increases the quality of analyst earnings forecasts, which is a key input to analyst valuations. Bandyopadhyay et al. (1995) also find that target price revisions are related to earnings forecast revisions, suggesting a link between target prices and earnings forecasts. It also builds on Mohanram's (2014) finding that there is a direct link between cash flow forecasts and stock prices. This suggests that there

[3] This is consistent with findings in Bradshaw (2002), Demirakos et al. (2004) and Asquith et al. (2005).

should be a link between cash flow forecasts and analyst expectations of future stock prices, i.e., target prices. There is no direct evidence on whether cash flow forecasts are useful for analyst valuations. Target prices, in theory, are useful in predicting future stock returns beyond earnings forecasts. Therefore, if analyst cash flow forecasts are sophisticated and contain information incremental to earnings forecasts, target prices should reflect this, after controlling for their earnings forecasts.

This leads to our first hypothesis:

*H*1**:** *An analyst's target price is more accurate if the analyst also provides a cash flow forecast.*

We extend this to argue that target prices should reflect not only the presence of cash flow forecasts but also their quality. The process of forecasting target prices is subject to analyst judgement about how a firm creates value and how key value drivers are likely to change in the future. The quality of analysts' valuations should depend on how accurately they translate their forecasts of earnings, cash flows, and other fundamentals into target prices. The available evidence on how analysts' valuation input accuracy affects target price quality is limited to earnings. Bradshaw et al. (2012) find no relation between the past accuracy of analysts' earnings forecasts and target price accuracy. Gleason et al. (2013) find that inferior earnings forecasts reduce the profitability of target prices. Da et al. (2016) find that the investment value of target prices derives in part from analysts' superior ability to forecast earnings. Call et al. (2009) show that the accuracy of analyst earnings forecasts improves in the presence of cash flow forecasts. But there is no evidence on the effect of analyst cash flow forecast quality on target price accuracy. We argue that if analysts use cash flow forecasts, either directly or indirectly, as valuation inputs, then the quality of the valuation model input should affect the quality of their target price valuations. We hypothesize that target price accuracy is higher when cash flow forecast accuracy is higher. If the incremental information in analyst cash flow forecasts is relevant for valuation then the effect of cash flow forecasts on target prices should be stronger for more accurate cash flow forecasts. On the other hand, based on the evidence in Givoly et al. (2009) that analyst cash flow forecasts are not useful to market participants because of their low quality, cash flow forecasts may introduce additional bias to analysts' target prices. For example, overly optimistic cash flow forecasts may give rise to inflated target prices that exaggerate potential investment returns. Therefore, distinguishing between accurate and inaccurate cash flow forecasts is important to identify whether high quality cash flow forecasts result in higher quality target prices. We therefore test the following hypothesis.

*H*2**:** *An analyst's target price accuracy increases with the accuracy of the analyst's cash flow forecast.*

We finally argue that cash flow forecasts contain more relevant information for analyst valuations of more challenging-to-value firms where earnings are less informative for valuation. This argument derives from evidence in Demirakos et al. (2010) that analysts are more likely to use the DCF model when valuing small firms, high-risk firms, loss-making firms, and firms with a limited number of industry peers. We predict that the improvement in the accuracy of target prices accompanied by cash flow forecasts is greater for firms that are more challenging to value. Similarly, we predict the effect of cash flow forecast accuracy on target price accuracy is higher form more challenging-to-value firms and we test the following hypotheses,

*H*3*a***:** *The increase in the accuracy of target prices when accompanied by cash flow forecasts is greater for firms that are more challenging to value.*

*H*3*b***:** *The rate at which the accuracy of target prices increase with the accuracy of the analysts' cash flow forecast is greater for firms that are more challenging to value.*

In addition to our contribution to the analyst cash flow forecast literature, our tests of *H*1–*H*3 contribute to the literature on analysts' target prices. Recent studies observe that target prices are generally under-researched (e.g., Bradshaw et al., 2012). Previous research examines the factors that influence target price accuracy, including analyst optimism (Asquith et al. 2005), the number of reports an analyst publishes (Bonini et al. 2010), analyst valuation model choice (Demirakos et al. 2010), the text-based information depth of analyst reports (Kerl 2011), the collective reputation of analysts (Bonini et al. 2011), and past forecast accuracy (Bradshaw et al. 2012). The consistent result from these studies is the limited accuracy of analysts' target prices compared with their earnings forecast accuracy.[4]

The literature offers no conclusive evidence on the factors that improve analyst target price accuracy. Some studies find larger target price forecast errors associated with higher target price boldness (Demirakos et al. 2010, Kerl 2011), suggesting that analyst optimism reduces accuracy. On the other hand, Kerl (2011) find no effect of analyst affiliation on target price accuracy. Evidence on analyst ability is also limited. Bradshaw et al. (2012) find evidence of persistent differential forecasting ability, but report that the differential abilities are economically trivial. Using the number of equity reports that an analyst issues to proxy for analyst experience, Bonini et al. (2010) hypothesize that more experience leads to higher target price accuracy, following the learning curve hypothesis, but fail to find supporting evidence. Demirakos et al. (2010) present evidence of analyst ability to make intelligent valuation model choices. Their evidence suggests that analysts select a valuation model appropriate to the difficulty of the valuation task and that accuracy does not vary with valuation model choice after accounting for this.

[4] Asquith et al. (2005) find that 54.3% of target prices are achieved within the following twelve months. Kerl (2011) finds a corresponding target price accuracy of 56.5% for German stocks. Bonini et al. (2010) find an accuracy of 33.1% for Italian stocks. For US stocks, Bradshaw et al. (2012) report an accuracy of 45%.

The above studies neglect the effect of a fundamental determinant of analyst forecast quality, namely the quality of analyst information as reflected in their valuation model inputs (Pope, 2003). Even when analysts derive their target prices using rigorous valuation techniques, inaccurate forecasts of earnings or cash flows that serve as valuation model inputs can compromise target price quality. Our study is the first examination of whether the disclosure of cash flow forecasts by an analyst and the information content of the forecasts improve the analyst's target price accuracy.

There is a need to identify when target price accuracy improves because target prices are an important output of analyst reports. Examining the relation between cash flow forecasts and target prices helps improve our understanding of whether analysts use cash flow information in their valuations. If cash flow forecasts are irrelevant for analyst target prices, we should find no association between target price accuracy and cash flow forecast quality after controlling for earnings forecast quality. Alternatively, if cash flow forecasts are more than naïve extensions of earnings forecasts, then better information about expected future cash flows should translate into improved analyst valuations. We test this directly by examining whether cash flow forecasts improve analyst target price accuracy.

The existing evidence on how the quality of valuation inputs affects valuation outcomes is based on earnings forecasts. Gleason et al. (2013) find that the profitability of target prices derived from price/earnings to growth ratio (PEG) valuation is significantly lower than the profitability of target prices derived from residual-income valuation (RIV). They show that using low quality earnings forecasts as valuation model inputs reduces the profitability of analysts' target prices and the difference in profitability between the two valuations. This evidence, however, does not necessarily imply that when cash flow forecasts improve earnings forecasts, they also improve target price accuracy. The literature consistently finds that target prices are less accurate than earnings forecasts (e.g. Asquith et al. 2005; Bradshaw et al. 2012) and Bradshaw et al. (2012) find that past earnings forecast accuracy is unrelated to target price accuracy. Therefore, we cannot infer the results of our examination of how the quality of cash flow forecasts affects analysts' valuations from the results of prior research.

## 3. Data and sample

We obtain analyst data for target prices, cash flow forecasts, and earnings forecasts from the I/B/E/S Detail History U.S. Edition database for the period 2000–2010. We focus on one-year-ahead forecasts because cash flow forecasts on I/B/E/S are mostly annual. We restrict our analysis to cash flow forecast observations for which target prices and earnings per share forecasts are available on I/B/E/S.[5] We identify two subsamples in our analysis: a) analysts who simultaneously issue cash flow forecasts, earnings forecasts, and target prices, and b) analysts who issue only earnings forecasts and target prices. Observations that have a target price (TP) and a cash flow forecast (CFF) belong to the CFF group, while observations that have only a TP belong to the no-CFF group. We rely on I/B/E/S when determining whether an analyst issued a cash flow forecast for a particular firm.[6] To include an observation in the CFF group we require the cash flow forecast to be issued on the same day as the target price. According to prior research on target prices (e.g., Bilinski et al. 2013), analysts consider their latest EPS forecast to be outstanding when they issue a target price unaccompanied by an earnings forecast on I/B/E/S. However, as there is no prior literature that examines target prices and cash flow forecasts, we

[5] We merge cash flow forecast observations with target prices and earnings per share forecasts from the I/B/E/S detail file based on company ticker, estimator ID, analyst mask code, and announcement date.

[6] Call et al. (2009) assure through their communication with I/B/E/S that I/B/E/S makes available in its database all cash flow forecasts provided by analysts.

impose the strict requirement that a cash flow forecast must be available on I/B/E/S on the same date as the target price forecast.

We require observations to have actual earnings per share and cash flow per share for the year on I/B/E/S to calculate earnings and cash flow forecast accuracy at the analyst level. Additionally, we require observations to have a stock price three days before the date of the target price forecast exceeding $1 per share. We also require data on stock price at the end of the forecast horizon (that is 12 months after the target price date).[7] Moreover, to mitigate effects of extreme observations due to data errors or misaligned stock spilt factors, we delete the upper 1% tail of the distribution of observations based on the ratio of target price to actual price. To further eliminate any ambiguity regarding observations in the no-CFF group, we require that target price observations in the no-CFF group have no cash flow forecasts on I/B/E/S by the same analyst for the same firm up to 90 days before the target price announcement date.

For each observation in the CFF group, we calculate the cash flow forecast error (inverse accuracy) at the analyst level as the absolute value of the difference between the cash flow forecast and actual cash flow per share as reported by the IBES Detail History – Actuals file for the relevant end of forecast period, divided by stock price at the forecast date.[8] We similarly calculate the earnings forecast error at the analyst level as the absolute difference between the analyst's earnings forecast and actual earnings for the year as reported by I/B/E/S, divided by stock price at the forecast date. Consistently, we calculate target price accuracy as the absolute value of the difference between the target price and the stock price at the end of the target price

[7] Market price data are from CRSP. Financial statement information and footnote data used later in the analysis are from Compustat.
[8] Appendix 1 provides precise definitions of all the variables in the main analysis.

forecast horizon divided by the current market price.[9] As Demirakos et al. (2010) explain, it is more meaningful to interpret accuracy in terms of the absolute forecast error than the signed forecast error. The signed forecast error can be difficult to interpret depending on whether the target price is above or below the market price. Other measures of target price accuracy such as measuring whether a target price is met within or at the end of the forecast horizon are less consistent with our measures of cash flow and earnings forecast accuracy.

Table 1 provides descriptive statistics on sample size, analyst and brokerage representation, and industry composition. The table shows that the sample represents 4,230 firms, 6,756 security analysts, and 561 research departments and comprises 408,040 observations. The number of observations including a CFF is 42,791, comprising about 10 percent of the sample and covering 2,042 firms and 1,729 analysts working for 268 brokerage houses. The number of observations in the CFF group increases each year consistent with previous studies.[10] The proportion of CFF observations in the total sample increases from 5% in 2000, to 12% in 2005, and to 14% in 2010. The number of firms receiving cash flow forecasts also increases from 11% of all firms in the sample in 2000 to 50% in 2010. Only 7% of all analysts provide cash flow forecasts in 2000 while this percentage increases to 27% by 2010.

## 4. Research design

We want to measure the impact of disclosing a CFF on an analyst's TP accuracy. Since we do not observe the counterfactual TP accuracy (i.e., the no-CFF TP accuracy for a CFF observation), we cannot evaluate the effects of a CFF by comparing outcome differences for a

[9] The literature uses several target price accuracy measures (see, for example, Asquith et al., 2005; Demirakos et al., 2010; Bradshaw et al., 2012; Bonini et al., 2010). We follow Demirakos et al. (2010) in calculating our (inverse) accuracy measure.

[10] The percentage of CFF observations is lower than in previous literature because we require our sample observations to include a target price issued on the same day as the cash flow forecast. This does not imply that analysts are less likely to issue cash flow forecasts when they publish target prices.

given treatment. Previous studies suggest that the analyst decision to provide a CFF is not random, so that the impact of a CFF on TP accuracy is unlikely to be homogeneous. Consequently, estimating the effect of a CFF on TP accuracy using ordinary least squares (OLS) is biased and suffers from identification problems. To eliminate the selection bias, we use propensity score-matching to balance observed differences between groups. We then run a multivariate regression on the matched sample to achieve higher efficiency. This combined analysis should be more robust and has the potential to significantly improve the quality of the results.

To compute the propensity scores, we first estimate the probability that a firm–analyst observation includes a CFF using the following logistic regression,

$$\begin{aligned}
&\Pr(CFF_i = 1) = \\
&\beta_0 + \beta_1 Accrual_i + \beta_2 AltmanZ_i + \beta_3 Capital_i + \beta_4 MCap_i + \beta_5 EVol_i + \beta_6 Freq_i \\
&+\beta_7 Star_i + \beta_8 InstOwn_i + \beta_9 nAnal_i + \beta_{10} Lag_EPSerr_i + \beta_{11} StrBuy_i + \beta_{12} Buy_i \\
&+\beta_{13} Sell_i + \beta_{14} Lev_i + Year\ fixed\ effects + u_i
\end{aligned} \tag{1}$$

The propensity score model estimates the conditional probability of a CFF given observable characteristics of analysts and firms. *CFF* is a dummy variable that indicates whether observation *i* includes a cash flow forecasts along with the analyst's target price and earnings forecast.[11] The explanatory variables are the covariates determining the analyst decision to forecast cash flows. The first set of explanatory variables follows DeFond and Hung's (2003) investor demand hypothesis. The magnitude of accruals (*Accruals*) captures the degree of earnings uncertainty. Because accruals are based on managerial estimates, large accrual-based

[11] Our definition of the CFF dummy differs from Call et al.'s (2009) definition. We require an observation to have a target price, an earnings forecast, and a cash flow forecast all issued on the same date by the same analyst to include it in the CFF group.

earnings increase market suspicion.[12] The availability of cash flow information helps validate whether large earnings are consistent with operating cash flows or whether they are financially engineered. Hence, cash flow forecasts should be more valuable for interpreting the information in earnings in the presence of large accruals. Altman's *Z*-score (*AltmanZ*) measures a firm's financial health, where lower *Z*-scores indicate worse financial health (Altman, 1968). Cash flow forecasts provide information on liquidity, solvency, and credit and bankruptcy risks. Therefore, cash flow forecasts should be more important for assessing the value of firms in worse financial health. Capital intensity (*Capital*) is the level of fixed assets in a firm. When capital intensity is high, firms rely on operating cash flows to fund the maintenance and replacement of existing assets. Cash flow forecasts should be more useful for firms with high capital intensity to assess their ability to meet cash needs. The natural logarithm of the firm's equity market value (*MCap*) controls for a firm's information environment. Earnings volatility (*EVol*) is a measure of earnings quality. When earnings volatility is high, investors perceive earnings quality to be low and the market requires additional information to assess the persistence of earnings components.

The second set of explanatory variables controls for analyst characteristics. We include variables related to analyst incentives: analyst forecasting frequency (*Freq*), an institutional investor star analyst dummy (*Star*), institutional ownership (*InstOwn*), and the number of analysts following the firm (*nAnal*). Analysts who make more frequent revisions are less likely to herd (Clement and Tse, 2005; Jegadeesh and Kim, 2010).[13] The literature uses Star analyst

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[12] We follow DeFond and Hung (2003) in measuring accruals as an absolute value. This is because we are interested in the association between an analyst's incentive to disclose a cash flow forecast and whether net income is significantly different from operating cash flows, regardless of whether the difference is positive or negative. Using a signed accrual measure would result in a different interpretation of the coefficient on the accruals variable. A signed accrual does not capture the size of managerial bias as it treats observations with large negative accruals differently from observations with large positive accruals.

[13] Evgeniou et al. (2010) show that low ability analysts tend to herd when information uncertainty is low while they deviate significantly from the consensus when information uncertainty is high. In contrast, high ability analysts tend not to change their degree of deviation from the consensus when information uncertainty is high. Evgeniou et al.

ranking to proxy for analyst quality and reputation. Previous research shows a positive relation between forecast accuracy and analyst reputation (Stickel, 1992). Institutional ownership in a firm and the number of analysts following provide measures of the firm's information environment. Analysts are also less likely to bias their forecasts for stocks that are highly visible to institutional investors. We expect analyst past earnings forecast error (*Lag_EPSerr*) to affect their decision to make cash flow forecasts. Building on the demand hypothesis, we expect analysts to provide cash flow forecasts when earnings are more difficult to forecast.

We include stock recommendation categories (*StrongBuy*, *Buy*, *Sell*) to control for the sensitivity of analysts' decision to make cash flow forecasts to their recommendations. We include leverage (*Lev*) to control for a firm's financial structure.[14] Finally, we include year fixed effects to control for any temporal factors that affect all firm–analyst observations in a given year equally.

Using propensity score matching, we match CFF to no-CFF observations based on the estimated propensity score. We then estimate the following multivariate regression of the effect of CFF on TP accuracy on the matched sample,

$$\begin{aligned}
&TPerr_i = \\
&\beta_0 + \beta_1 CFF_i + \beta_2 Accrual_i + \beta_3 AltmanZ_i + \beta_4 Capital_i + \beta_5 MCap_i + \beta_6 EVol_i \\
&+\beta_7 Freq_i + \beta_8 Star_i + \beta_9 InstOwn_i + \beta_{10} nAnal_i + \beta_{11} EPSerr_i + \beta_{12} StrBuy_i \\
&+\beta_{13} Buy_i + \beta_{14} Sell_i + \beta_{15} Lev_i + Fixed\ effects + u_i
\end{aligned} \quad (2)$$

The dependent variable is our measure of inverse target price accuracy (*TPerr*). The parameter of main interest in this model is $\beta_1$; our first hypothesis predicts that if target price observations with cash flow forecasts are more accurate, we should observe a negative coefficient on the *CFF* dummy. A negative coefficient suggests that target price error is lower

suggest that low ability analysts are willing to take a risk when information uncertainty is high because high ability analysts are also likely to have high forecast errors due to the uncertain information environment.

[14] Appendix 1 provides precise definitions of all the variables in the main analysis.

for observations that have analyst cash flow forecasts, compared with the target price error of observations with no cash flow forecasts. The right hand side of equation (2) includes controls for variables affecting the analyst decision to issue cash flow forecasts (*Accrual*, *AltmanZ*, and *Capital*) that we discuss above. We also control for information uncertainty proxies that are likely to affect the complexity of the forecasting task and consequently target price accuracy: earnings volatility (*EVol*), the number of analysts following a firm (*nAnal*), and firm size (*MCap*).[15] To control for the effect of earnings forecast quality on target price accuracy we include *EPSerr*, the analyst's concurrent earnings per share forecast error. Other control variables relate to analyst incentives: an institutional investor star analyst dummy (*Star*) and institutional ownership (*InstOwn*). Stock recommendation categories (*StrongBuy*, *Hold*, *Sell*) again control for the sensitivity of target price accuracy to analyst recommendations and leverage (*Lev*) controls for a firm's financial structure. In this, and in all subsequent regressions unless otherwise indicated, we include analyst, firm, and year fixed effects and calculate *p*-values based on standard errors clustered by analyst and firm.

To test our second hypothesis of whether cash flow accuracy is associated with analyst target price accuracy, we estimate the following multivariate regression of target price accuracy on cash flow forecast accuracy.

$$\begin{aligned} &TPerr_i = \\ &\beta_0 + \beta_1 CFFerr_i + \beta_2 Accrual_i + \beta_3 AltmanZ_i + \beta_4 Capital_i + \beta_5 MCap_i + \beta_6 EVol_i \\ &+\beta_7 Freq_i + \beta_8 Star_i + \beta_9 InstOwn_i + \beta_{10} Lev_i + \beta_{11} EPSerr_i + \beta_{12} StrBuy_i \\ &+\beta_{13} Buy_i + \beta_{14} Sell_i + \beta_{15} nAnal_i + Fixed\ effects + u_i \end{aligned} \tag{3}$$

*CFFerr* is the cash flow forecast error (inverse accuracy). Our second hypothesis predicts a positive coefficient on the cash flow forecast error, indicating that target prices are more accurate

[15] Evidence on the effect of company size on target price accuracy is mixed. Some research shows that size reduces forecast accuracy (Bonini et al., 2010) while other research finds that target prices are more accurate for larger companies (Demirakos et al., 2010; Kerl, 2011).

when analysts make more accurate cash flow forecasts. The other right-hand side variables of equation (3) are the same as the control variables of equation (2).

We next test hypothesis H3a, that the *increase in the accuracy* of target prices when accompanied by cash flow forecasts is greater for challenging-to-value firms than for non-challenging firms. We introduce the dummy variable *Challenging*, which equals 1 if an observation belongs to the group of firms that are more challenging to value. We follow Demirakos et al. (2010) and define challenging firms based on firm size, firm risk, profitability, and the number of industry peers. We estimate the following equation:

$$\begin{aligned}
&TPerr_i = \\
&\beta_0 + \beta_1 CFF + \beta_2 Challenging_i + \beta_3 CFF \times Challenging_i + \beta_4 Accrual_i \\
&+\beta_5 AltmanZ_i + \beta_6 Capital_i + \beta_7 MCap_i + \beta_8 EVol_i + \beta_9 Freq_i + \beta_{10} Star_i \\
&+\beta_{11} InstOwn_i + \beta_{12} nAnal_i + \beta_{13} EPSerr_i + \beta_{14} StrBuy_i + \beta_{15} Buy_i \\
&+\beta_{16} Sell_i + \beta_{17} Lev_i + Fixed\ effects + u_i
\end{aligned} \tag{4}$$

The coefficient on the interaction, $CFF \times Challenging$, tests whether the improvement in target price accuracy in moving from the no-CFF to the CFF group is greater for challenging-to-value firms. A negative coefficient supports our hypothesis that the benefit of cash flow forecast availability for target price accuracy of challenging firms is greater than for non-challenging firms.

We then estimate equation (5) to test hypothesis H3b, that the effect of cash flow forecast accuracy on *the accuracy* of target prices is greater for challenging-to-value firms.

$$\begin{aligned}
&TPerr_i = \\
&\beta_0 + \beta_1 CFFerr + \beta_2 Challenging_i + \beta_3 CFFerr \times Challenging_i + \beta_4 Accrual_i \\
&+\beta_5 AltmanZ_i + \beta_6 Capital_i + \beta_7 MCap_i + \beta_8 EVol_i + \beta_9 Freq_i + \beta_{10} Star_i \\
&+\beta_{11} InstOwn_i + \beta_{12} nAnal_i + \beta_{13} EPSerr_i + \beta_{14} StrBuy_i + \beta_{15} Buy_i \\
&+\beta_{16} Sell_i + \beta_{17} Lev_i + Fixed\ effects + u_i
\end{aligned} \tag{5}$$

In equation (5), which we estimate on the CFF observations, the coefficient on the interaction, $CFFerr \times Challenging$, tests whether the improvement in target price accuracy associated with a higher cash flow forecast accuracy within the CFF group is greater for challenging-to-value firms than for non-challenging firms. A positive sign on this coefficient supports our third hypothesis that the benefit of cash flow forecasts availability for target price accuracy of challenging firms is greater than for non-challenging firms.

## 5. Empirical estimation and results

### 5.1 Univariate analysis

Table 2 provides summary statistics for the variables in the model for the full sample. The average target price error in our sample is 47%, which is comparable to the target price error of 45% in Bradshaw et al. (2012). Summary statistics for variables determining cash flow forecast disclosure are consistent with those in DeFond and Hung (2003). Other variables are generally consistent with prior literature.[16] The summary statistics for all variables in the model raise no concerns for the implementation of the propensity score analysis.[17]

We conduct a univariate analysis of the differences in firm characteristics between observations with and without cash flow forecasts. Table 3, panel A compares the magnitude of accruals, *Z*-score, capital intensity, earnings forecast error, earnings volatility, institutional ownership, leverage, market capitalization, number of analysts following, and target price error for the two groups. The table also presents the results of mean and median differences tests between the two groups. On average, analysts issue cash flow forecasts for firms with larger

[16] Our earnings forecast error (*EPSerr*) summary statistics differ from Call et al.'s (2012) because Call et al. (2012) scale the absolute difference between the earnings forecast and the actual earnings by the earnings forecast, while we scale by the market price prior to announcement, consistent with how we compute our target price error. Call et al. (2012) do not present summary statistics for their cash flow forecast error variable.

[17] We indicate with an asterisk which variables are winsorized in Table 2 (descriptive statistics). We winsorize these variables at the upper and lower 1% levels to reduce outlier effects. We do not winsorize other variables because they do not suffer from outlier problems.

absolute accruals, lower *Z*-scores, higher capital intensity, larger earnings forecast error, higher earnings volatility, and larger market capitalization, consistent with previous findings in the literature. We also find that firms with cash flow forecasts have a larger analyst following and higher leverage and institutional ownership, on average. Moreover, target price accuracy is higher for firms with cash flow forecasts. These significant differences support our argument that the analyst decision to forecast cash flows is not random. The significant differences in means and medians ($p$ = 0.000) between the two groups also call for controlling using matching methods.

According to the correlation matrix of the variables (not tabulated), there is a high correlation between firm size and analyst following, as expected. The correlations between other variables do not raise any multicollinearity concerns for the regression analysis. Multicollinearity is not an issue for the propensity score matching estimation because estimating the effects of individual covariates is not its main aim.

We also conduct a univariate analysis of the difference in target price accuracy between observations with high and low cash flow forecast error (inverse accuracy). We classify observations below the 25$^{th}$ percentile of *CFFerr* as observations with low cash flow forecast error and observations above the 75$^{th}$ percentile as observations with high cash flow forecast error. Table 3, panel B presents the differences in means and medians between the two groups. The average target price error is 0.559 for observations in the high CFF error group, compared with 0.413 for the low CFF error group. The difference between the two means is significant as is the difference in median target price accuracy. This suggests that the unconditional target price accuracy is higher for observations with higher cash flow forecast accuracy. We also test the univariate difference in target price accuracy between observations with above and below mean cash flow forecast error of 0.03. Table 3, panel B shows that observations with above average CFF error have a mean target price error of 0.547 while observations with below average CFF error have a mean target price error of 0.417. Differences in means and medians between the two groups are significant.

*5.2 Multivariate analysis*

*5.2.1 The determinants of cash flow forecast disclosure*

Table 4 reports the results of the logistic regression estimation of equation (1) as well as the marginal effects of the independent variables on the probability of an analyst issuing a cash flow forecast. Consistent with DeFond and Hung (2003) and our univariate analysis, Altman's Z-score is negatively associated with the decision to disclose a CFF, while absolute accruals, earnings volatility, capital intensity, and size are positively associated with CFF disclosure, with change in capital intensity and the magnitude of accruals having the greatest impact. This suggests that analysts disclose cash flow forecasts for firms in weaker financial health, with more volatile earnings, higher capital intensity, and larger market capitalization. Moreover, the results indicate that analysts are more likely to provide cash flow forecasts for firms with higher institutional ownership and firms with a higher analyst following (i.e., more visible firms). Analysts are also more likely to provide cash flow forecasts for firms they cover more frequently. There is a negative association between analyst star ranking and the incidence of a cash flow forecast. This is a result that the literature has not been previously examined. A possible explanation is that analysts provide cash flow forecasts when they need to improve their earnings forecasts. If non-Star analysts are more likely to make lower quality earnings forecasts then they have greater incentives to supplement their earnings forecasts with cash flow forecasts. Moreover, contrary to our expectations, we find a negative relation between an analyst's past earnings forecast error and cash flow forecast disclosure. Again, this is a result that the literature has not previously examined. It implies that analysts who make cash flow forecasts have higher past earnings forecast accuracy.

We use the results of the logistic regression to estimate the propensity score for each observation in our sample. The propensity score is the conditional probability of an analyst providing a cash flow forecast for a particular observation. We use the propensity score to identify matched pairs of observations in the CFF and no-CFF groups.[18] We then assess the covariate balance between the matched observations using several measures. We conduct *t*-tests of the equality of means in the CFF and no-CFF groups after matching. Untabulated results indicate that the matching algorithm successfully balances all of the covariates; all *t*-tests are insignificant ($p > 0.1$). This is consistent with tests based on the standardized bias and the reduction in bias achieved after matching; the standardized bias is the difference in the sample means of the CFF and no-CFF groups as a percentage of the square root of the average of the sample variances in the two groups. After matching, the bias falls significantly for most covariates. Therefore, the matched sampling methodology helps reduce bias due to observed covariates. We combine this propensity score matching method with regression adjustments as an effective method for ensuring that we eliminate differences in the propensity scores while using information about the association between the different covariates and the dependent variable.[19]

[18] We perform this matching with *psmatch2* of Leuven and Sianesi (2003), which uses a nearest-neighbour matching method, beginning with the treated subject with the highest (and thus most difficult to match propensity score) and proceeding to the subject with the lowest propensity score. The results are not sensitive to this choice of matching method.

[19] Regression-adjusted matching is an extension of classical matching. It combines matching on the propensity score with regression adjustment on covariates. Because we implement a 1-to-N matching method, we do not lose any observations from our no-CFF sample. Therefore, we are able to perform the regression-adjusted matching estimation on the full sample after matching.

*5.2.2. The effect of cash flow forecast availability on target price accuracy*

Table 5 reports the results of estimating equation (2) to test our first hypothesis of the association between cash flow forecast availability and target price accuracy. Column 1 reports the results of OLS estimation without matching or controls for selection bias. The results show no significant association between cash flow availability and target price error while the effect of earnings forecasts error is significant with a coefficient of 0.716 ($p$ = 0.000). The coefficients on the other covariates suggest that target price error falls for firms with higher institutional ownership and for larger firms. On the other hand, target price error is higher for Star analysts and when the analyst revises her forecast for a firm more frequently. Target price error is also higher for firms with more volatile and uncertain earnings and a larger analyst following.

The above results based on OLS suffer from a selection bias because the analyst decision to provide a CFF is not random. To eliminate the selection bias, we use the matched sample from the propensity score estimation and combine it with regression adjustments. Columns 2–3 report the estimation of the model after matching. Combining regression with matching involves running the chosen regression model with the matched observations from the CFF and no-CFF groups with the propensity scores included as covariates in the regression. This regression-adjusted matching can protect against bias from model misspecification.[20]

Column 2 estimates results using a propensity score linear model. Column 3 repeats the estimation of column 1 using OLS with the matched sample. The results in columns 2 and 3 suggest that target price error falls in the presence of cash flow forecasts, even after controlling for the earnings forecast error. The coefficients on *CFF* are −0.044 and −0.055, both significant

[20] The propensity score matching method (without regression adjustment) assumes that the functional form of the propensity score regression model is correctly specified.

with $p$ = 0.000. The results suggest that the availability of cash flow forecasts is associated with a reduction in analyst target price forecast error, consistent with our first hypothesis.

*5.2.3. The effect of cash flow forecast error on target price accuracy*

To test our second hypothesis, we estimate equation (3) on the sample of analyst observations that include a cash flow forecast. When we conduct this estimation the sample size falls to 38,650 observations because out of 42,791 observations in the CFF group, there are 4,141 observations for which I/B/E/S does not report an actual cash flow for the forecast period end date. Since we need the actual cash flow to calculate the cash flow forecast error, we eliminate observations with no actual cash flows on I/B/E/S. We choose not to use actual cash flows from Compustat because Givoly et al. (2009) note discrepancies between the actual cash flow that I/B/E/S and Compustat report in 96.5 percent of cases. Table 6 presents the results of the estimation. Consistent with our prediction, the coefficient on *CFFerr* of 0.791 ($p$ = 0.000) suggests that analysts' target prices are more accurate when accompanied by more accurate cash flow forecasts.[21]

The above results offer statistically significant evidence on the usefulness of analyst cash flow forecasts for target prices. Our results are also economically significant. First, using the coefficient on *CFF* from table 5, column 3, changing CFF from zero to one reduces the mean target price error by 9.4%. Second, a one standard deviation increase in *CFFerr* increases the target price error by 395.50 basis points and the mean target price error by 7.5%. By comparison, Call et al. (2009) find that analysts who make cash flow forecasts improve their earnings forecast

[21] We repeat the estimation of equation (3), replacing *CFFerr* with a binary variable that takes the value 1 if analyst cash flow forecasts have a forecast error above the average *CFFerr* and zero otherwise. The results are consistent with those in table 6, suggesting that observations with above average cash flow forecast errors have higher target price forecast errors.

accuracy by 0.6% compared to the average analyst covering the firm. The estimates we find for the effect of cash flow forecasts on target price accuracy are an order of magnitude higher.

We re-estimate equation (2) using an analyst-specific analysis. We examine the accuracy of target prices by an analyst who issues target prices and cash flow and earnings forecasts for some firms but issues only target prices and earnings forecasts for other firms. We expect target prices accompanied by cash flow forecasts to be more accurate than unaccompanied target prices. This analysis mitigates concerns over the effect of analyst characteristics that might affect forecast accuracy and an analyst's decision to issue a cash flow forecast that our previous analysis does not capture. In table 7, we estimate equation (2) for each analyst separately, for a total of 6,756 unique regressions. We report the mean coefficients and their corresponding $p$-values. We also report the average adjusted $R^2$ across all 6,756 regressions.

The mean coefficient on *CFF* is significantly negative (−0.070, $p$ = 0.000). This suggests that, relative to unaccompanied target prices, when analysts accompany their target prices with cash flow forecasts, their target prices error falls on average by 14.9%. This result is consistent with our pooled cross-sectional analysis and suggests that analysts issue more accurate target prices when they also issue cash flow forecasts.[22]

*5.2.4. Target price accuracy of firms that are more challenging to value*

To test our third hypothesis, we estimate equation (4) on the CFF sample. Based on evidence in Demirakos et al. (2010), we first use loss-making firms as a proxy for firms that are more challenging to value. In table 8, the dummy variable *Challenging* of equation (4) equals 1 if the firm is loss-making in the year before the forecast announcement, if the firm has a limited

[22] We repeat the analysis requiring an analyst to provide a cash flow forecast for at least one of the companies she covers in a year in order to include her in this analysis and find that our results also hold.

number of industry peers in the sample, if the firm is small or if the firm has a high risk level, and zero otherwise. Table 8, column 1 presents the results of estimating equation (4). The coefficient on *CFF* is negative (−0.038, $p$ = 0.000) suggesting that cash flow forecast availability reduces target price error for non-challenging firms. Table 8 also shows that the coefficient on the interaction term *CFF* × *Challenging* is negative (−0.020, $p$ = 0.000). This implies that the increase in accuracy of target prices accompanied by cash flow forecasts over target prices without cash flow forecasts is greater for challenging-to-value firms than for non-challenging firms. This evidence supports our hypothesis H3a.

Table 8, column 2 presents the estimation results of equation (5). The coefficient on *CFFerr* is positive (0.353, $p$ = 0.000) suggesting that cash flow forecast error increases target price error for non-challenging firms. The coefficient on the interaction term *CFFerr* × *Challenging* is positive (0.763, $p$ = 0.000). Consistent with the prediction of hypothesis H3b, the association between target price error and cash flow forecast error is larger for firms that are more challenging to value.

*5.2.5. Target price accuracy of analysts who switch cash flow disclosure*

Motivated by Call et al. (2009), we use an interrupted time-series specification to estimate the effect of cash flow forecast availability on target price accuracy of a subsample of analysts who initiate the provision of cash flow forecasts for a firm. For this analysis, we retain only one observation for each analyst–firm pair in a year and estimate equation (2) including observations only for the year before and the year of the provision switch for each pair. We identify 2,066 cases (for 512 analysts) representing a switch from provision to non-provision of a cash flow forecast. The results (not tabulated) give an insignificant coefficient on *CFF* of −0.032 ($p$ = 0.249). When, like Call et al. (2009), we restrict this sample to observations for which the analyst continues to provide cash flow forecasts for more than one future year, the number of switches reduces to 519 by 172 analysts. Repeating the regression on this sample gives a significant coefficient on *CFF* (−0.1572, $p$ = 0.007), whereas the coefficient on *CFF* for the "one-off" switchers remains insignificant at −0.043 ($p$ = 0.571). These results suggest that analysts who switch from not providing cash flow forecasts for the firm to providing a cash flow forecast, improve their target price accuracy only when they continue to provide cash flow forecasts in later years.[23]

## 6. Additional analysis

We undertake several sensitivity tests of our hypotheses H1 and H2 and report the results in table 9.[24] Bradshaw et al. (2012) find that target prices tend to be more accurate in up than down markets. We test the sensitivity of our results to this control. Similar to Bradshaw et al. (2012), we use the sign of the realized S&P500 return over the forecast horizon to classify up and down markets. Up markets span the second halves (July–December) of 2002–2006, 2008, and 2009. All other periods are down markets. We add the variable *Up*, which takes the value 1 for up markets and zero otherwise, to equations (2) and (3). Consistent with previous findings, *Up* is negatively associated with target price error, confirming evidence that target price error is lower during up markets. However, the results do not affect the sign or magnitude of the coefficients on our main variables, *CFF* and *CFFerr*, in equations (2) and (3) (table 9, columns 1–2). We also test the sensitivity of our results to controlling for temporal effects and for previous findings that

[23] Estimating equivalent regressions on samples of analysts who cease providing cash flow forecasts gives insignificant coefficients on *CFF*. These regressions and those we refer to in the main text in this subsection have much lower sample sizes compared with Call et al. (2009) due to our requirement for observations to have target prices.

[24] Table 9 reports the coefficients and $p$-values corresponding to *CFF* and *CFFerror* for the sensitivity tests we conduct. All estimations, however, include the covariates in our preceding analysis from equations (2) and (3).

cash flow forecast accuracy declines over time. In addition to the year fixed effects that we include in all of main estimations, we introduce two control variables *HorizonCF* for cash flows and *HorizonTP* for target prices, where *Horizon* equals the number of months to the end of the forecast period. Adding these two control variables and re-estimating equation (3) does not affect our results and *HorizonCF* and *HorizonTP* have insignificant coefficients since we already control for year fixed effects (table 9, column 3).

We also test the sensitivity of our results to alternative explanations for why analysts make cash flow forecasts. Givoly et al. (2009) challenge the validity of DeFond and Huang's (2003) demand hypothesis. Our paper does not set out to test the demand hypothesis, rather we use the results from the demand hypothesis only to identify control variables that, based on theory, are likely to affect the analyst decision to report a CFF. Table 4 shows that all the demand hypothesis variables are significant, so the choice to include a CFF or not appears to have a rational theoretical underpinning. Givoly et al., however, argue that market demand may not be the major reason for the increasing availability of cash flow forecasts. For example, they point out a strong industry concentration in the availability of cash flow forecasts, with the energy industry having the highest concentration. We examine whether removing observations from the Energy sector affects our tests of H1 and H2 to check if this industry drives our results. Doing this does not change the results we report in the main analysis (table 9, columns 4–5).

In addition to the above concerns, Givoly et al. (2009) argue that the availability of cash flow forecasts simply follows an upward time trend. We therefore test whether our results hold if we estimate our regressions on three samples: the first covers 2000 to 2003, during which there are fewer cash flow forecast observations than in later periods. The second covers 2004 to 2006 and the third 2007 to 2010. We find consistent results with coefficients on *CFF* and *CFFerr* having the same sign and significance as the estimation on the full sample (table 9, columns 6–11). This suggests that changes occurring over time do not drive our results.

The analysis to this point compares analyst target price accuracy accompanied or unaccompanied by a cash flow forecast. However, there are instances when an analyst provides a target price unaccompanied by a cash flow forecast but for a firm that has cash flow forecasts by other analysts in the forecast period. We therefore test the sensitivity of our results to the availability of cash flow forecasts by other analysts for a particular firm. We add the control variable *Other-CFF*, which takes the value 1 if a firm for a particular observation receives cash flow forecasts by another analyst in the forecast period, and zero otherwise. This additional control provides insights into whether the target price accuracy of analysts who do not issue cash flow forecasts benefit from the availability of other analysts' cash flow forecasts. It also controls for evidence on the effect of general cash flow forecast availability in correcting mispricing (Mohanram, 2014; Radhakrishnan and Wu, 2014). We find that our main results are unaffected by including this additional control variable. The results (not tabulated) remain significant after matching and have the expected sign and magnitude. The control *Other-CFF* has a significant negative coefficient, indicating that the availability of cash flow forecasts by other analysts provides additional improvement in analyst target price accuracy.

## 6. Conclusion

Our study contributes to grown evidence that the issuing of cash flow forecasts by analysts has positive capital market consequences. We investigate whether analyst cash flow forecasts are useful for their valuations. While analysts' decision processes and how they perform their analysis and estimate target prices are unobservable, our study explores the effect of analyst cash flow forecasts as a valuation input on target prices. We investigate whether analysts' target prices are more accurate when they issue cash flow forecasts than when they do not. Additionally, we predict that an analyst's target price accuracy is higher when the analyst discloses a more accurate cash flow forecast. We model the relation between analyst target price accuracy and cash flow forecast disclosure and also between target price accuracy and cash flow forecast quality. We analyze a sample of US stocks with target prices and cash flow forecasts on I/B/E/S between 2000 and 2010 and find a positive association between analysts' cash flow disclosure and target price accuracy. The effect of cash flow forecast availability on target price accuracy is significantly larger for higher quality cash flow forecasts. Our results also show that the increase in target price accuracy when analysts make cash flow forecasts is greater for firms that are more challenging to value. Consistently, we find that the rate at which the accuracy of target prices increase with the accuracy of the analysts' cash flow forecast is greater for firms that are more challenging to value.

Our study is the first to examine the effect of cash flow disclosure and quality on target price accuracy and contributes to our understanding of the link between cash flow forecast disclosures and target prices. Forecasting cash flows can be a sophisticated process, involving the use and processing of accounting information. Studying the implications of this process for valuation is essential to understanding how analysts, as financial intermediaries, perform their job of facilitating the flow of information to the capital market. Awareness of how the quality of valuation model inputs affects analysts' stock valuations is of interest to a broad audience of investors, companies, researchers, and analysts.

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**Table 1**
**Descriptive statistics for sample size and analyst and research department representation**

| | Full Sample | CFF Sample | No-CFF Sample |
|---|---|---|---|
| Companies | 4,230 | 2,042 | 4,212 |
| Analysts | 6,756 | 1,729 | 6,613 |
| Research departments | 573 | 268 | 561 |
| Observations | 408,040 | 42,791 | 365,249 |

| | Companies | | | Analysts | | | Observations | | |
|---|---|---|---|---|---|---|---|---|---|
| Year | Full Sample | CFF Sample | no-CFF Sample | Full Sample | CFF Sample | no-CFF Sample | Full Sample | CFF Sample | no-CFF Sample |
| 2000 | 1,920 | 211 | 1,914 | 1,985 | 134 | 1,967 | 18,306 | 860 | 17,446 |
| 2001 | 1,877 | 131 | 1,875 | 2,152 | 117 | 2,147 | 22,771 | 543 | 22,228 |
| 2002 | 1,892 | 188 | 1,889 | 2,292 | 165 | 2,284 | 28,319 | 844 | 27,475 |
| 2003 | 1,980 | 612 | 1,975 | 2,062 | 359 | 2,033 | 30,914 | 2,350 | 28,564 |
| 2004 | 2,087 | 735 | 2,067 | 2,196 | 468 | 2,150 | 33,914 | 3,448 | 30,466 |
| 2005 | 2,204 | 847 | 2,186 | 2,199 | 435 | 2,152 | 33,644 | 4,036 | 29,608 |
| 2006 | 2,275 | 917 | 2,252 | 2,223 | 460 | 2,161 | 36,261 | 3,878 | 32,383 |
| 2007 | 2,303 | 951 | 2,280 | 2,255 | 482 | 2,200 | 39,900 | 4,306 | 35,594 |
| 2008 | 2,282 | 1,024 | 2,261 | 2,291 | 507 | 2,219 | 51,827 | 6,611 | 45,216 |
| 2009 | 2,226 | 1,064 | 2,212 | 2,290 | 543 | 2,216 | 53,026 | 7,524 | 45,502 |
| 2010 | 2,225 | 1,115 | 2,209 | 2,571 | 688 | 2,440 | 59,158 | 8,391 | 50,767 |

**Notes:**
The table presents the sample distribution by cash flow forecast availability for companies, analysts, and research departments and the sample observations by year for the full sample, the cash flow forecast (CFF) sample and the no cash flow forecast (no-CFF) sample.

**Table 2**
**Descriptive Statistics**

| Variable | N | Mean | Std. Dev. | Min | 25$^{th}$ | Median | 75th | Max |
|---|---|---|---|---|---|---|---|---|
| *Accrual* | 408,040 | 0.09 | 0.13 | 0.00 | 0.03 | 0.06 | 0.10 | 11.45 |
| *AltmanZ** | 408,040 | 5.75 | 6.50 | −2.74 | 2.18 | 3.82 | 6.70 | 39.07 |
| *Buy* | 408,040 | 0.34 | 0.48 | 0.00 | 0.00 | 0.00 | 1.00 | 1.00 |
| *Capital** | 408,040 | 0.94 | 1.36 | 0.00 | 0.23 | 0.41 | 0.91 | 7.88 |
| *CFFerr** | 38,650 | 0.03 | 0.05 | 0.00 | 0.01 | 0.02 | 0.04 | 0.35 |
| *CFF* | 408,040 | 0.10 | 0.31 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 |
| *EPSerr* | 408,040 | 0.05 | 0.13 | 0.00 | 0.02 | 0.03 | 0.05 | 21.94 |
| *EVol* | 408,040 | 2.64 | 1.84 | −4.73 | 1.31 | 2.55 | 3.89 | 11.12 |
| *Freq* | 408,040 | 4.25 | 2.63 | 1.00 | 2.00 | 4.00 | 5.00 | 33.00 |
| *Hold* | 408,040 | 0.33 | 0.47 | 0.00 | 0.00 | 0.00 | 1.00 | 1.00 |
| *InstOwn* | 408,040 | 0.71 | 0.22 | 0.00 | 0.59 | 0.75 | 0.87 | 1.00 |
| *Lev* | 408,040 | 0.21 | 0.21 | 0.00 | 0.03 | 0.18 | 0.32 | 4.99 |
| *Lag_EPSerr* | 408,040 | 0.04 | 0.04 | 0.00 | 0.01 | 0.03 | 0.05 | 0.27 |
| *MCap* | 408,040 | 14.70 | 1.71 | 7.14 | 13.48 | 14.61 | 15.86 | 20.06 |
| *nAnal* | 408,040 | 13.23 | 7.97 | 1.00 | 7.00 | 12.00 | 18.00 | 53.00 |
| *Sell* | 408,040 | 0.01 | 0.12 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 |
| *Star* | 408,040 | 0.17 | 0.38 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 |
| *StrBuy* | 408,040 | 0.26 | 0.44 | 0.00 | 0.00 | 0.00 | 1.00 | 1.00 |
| *TPerr** | 408,040 | 0.47 | 0.53 | 0.01 | 0.15 | 0.34 | 0.63 | 11.00 |

**Notes:**
Summary statistics for all variables in the study. Asterisked variables are winsorized at the upper and lower 1% levels to reduce outlier effects. Appendix 1 gives variable definitions.

**Table 3**
**Panel A: Comparison of firm characteristics**

| | Mean | | Median | | Mean difference | | Median difference | |
|---|---|---|---|---|---|---|---|---|
| | CFF<br>$N$ = 42,791 | No-CFF<br>$N$ = 365,249 | CFF<br>$N$ = 42,791 | No-CFF<br>$N$ = 365,249 | $t$-stat | $p$-value | $z$-stat | $p$-value |
| *Accrual* | 0.100 | 0.085 | 0.074 | 0.060 | −22.7 | 0.000 | −44.2 | 0.000 |
| *AltmanZ* | 3.971 | 5.955 | 2.791 | 3.964 | 60.1 | 0.000 | 76.6 | 0.000 |
| *Capital* | 2.130 | 0.803 | 1.090 | 0.385 | −200.0 | 0.000 | −133.3 | 0.000 |
| *EPSerr* | 0.053 | 0.047 | 0.039 | 0.033 | −8.9 | 0.000 | −43.8 | 0.000 |
| *EVol* | 3.133 | 2.578 | 3.079 | 2.492 | −59.4 | 0.000 | −58.1 | 0.000 |
| *InstOwn* | 0.730 | 0.704 | 0.773 | 0.749 | −22.4 | 0.000 | −21.6 | 0.000 |
| *Lev* | 0.241 | 0.207 | 0.226 | 0.176 | −32.6 | 0.000 | −47.7 | 0.000 |
| *MCap* | 15.013 | 14.661 | 14.993 | 14.561 | −40.4 | 0.000 | −44.6 | 0.000 |
| *nAnal* | 15.400 | 12.978 | 14.000 | 12.000 | −2.5 | 0.000 | −61.1 | 0.000 |
| *TPerr* | 0.452 | 0.469 | 0.328 | 0.337 | 6.4 | 0.000 | 3.7 | 0.000 |

**Panel B: Comparison of target price accuracy with cash flow forecast accuracy**

| | Mean | | Median | | Mean difference | | Median difference | |
|---|---|---|---|---|---|---|---|---|
| | High *CFFerr*<br>*Above 75th percentile* | Low *CFFerr*<br>*Below 25th percentile* | High *CFFerr*<br>*Above 75th percentile* | Low *CFFerr*<br>*Below 25th percentile* | | | | |
| *Obs.* | 9,663 | 9,663 | | | $t$-stat | $p$-value | $z$-stat | $p$-value |
| *TPerr* | 0.559 | 0.413 | 0.379 | 0.316 | −18.9 | 0.000 | −14.2 | 0.000 |
| | Above average *CFFerr* | Below average *CFFerr* | Above average *CFFerr* | Below average *CFFerr* | $t$-stat | $p$-value | $z$-stat | $p$-value |
| *Obs.* | 11,010 | 27,640 | | | | | | |
| *TPerr* | 0.547 | 0.417 | 0.374 | 0.313 | −24.6 | 0.000 | −16.8 | 0.000 |

**Notes:**

Panel A: A comparison of the characteristics of companies with and without cash flow forecasts, giving the means of firm characteristics and the results of mean and median differences tests. Appendix 1 provides variable definitions.

Panel B: Univariate analysis of the difference in target price accuracy between observations with high vs. low cash flow forecast error (inverse accuracy). High *CFFerr* denotes observations above the 75th percentile of *CFFerr* (i.e., observations with high cash flow forecast error). Low *CFFerr* denotes observations below the 25th percentile of *CFFerr* (i.e., observations with low cash flow forecast error). Above average *CFFerr* includes observations with *CFFerr* larger than the mean. Below average *CFFerr* includes observations with *CFFerr* below the mean.

**Table 4**
**Propensity-score estimation using logistic regression**

| *Dependent variable* | *Predicted sign* | *CFF* | *Marginal effect* |
|---|---|---|---|
| *Accrual* | + | 0.308*** | 0.022*** |
| | | [0.000] | [0.000] |
| *AltmanZ* | − | −0.031*** | −0.002*** |
| | | [0.000] | [0.000] |
| *Capital* | + | 0.448*** | 0.032*** |
| | | [0.000] | [0.000] |
| *MCap* | + | 0.039*** | 0.003*** |
| | | [0.000] | [0.000] |
| *EVol* | + | 0.022*** | 0.002*** |
| | | [0.000] | [0.000] |
| *Freq* | + | 0.042*** | 0.003*** |
| | | [0.000] | [0.000] |
| *Star* | + | −0.188*** | −0.013*** |
| | | [0.000] | [0.000] |
| *InstOwn* | + | 0.399*** | 0.029*** |
| | | [0.000] | [0.000] |
| *nAnal* | + | 0.016*** | 0.001*** |
| | | [0.000] | [0.000] |
| *Lag_EPSerr* | + | −0.403*** | −0.029*** |
| | | [0.083] | [0.000] |
| *StrBuy* | | −0.253*** | −0.018*** |
| | | [0.000] | [0.000] |
| *Buy* | | −0.093*** | −0.007*** |
| | | [0.000] | [0.000] |
| *Sell* | | −0.688*** | −0.049*** |
| | | [0.000] | [0.000] |
| *Lev* | | −0.579*** | −0.042*** |
| | | [0.000] | [0.000] |
| Year fixed effects | | Yes | |
| Pseudo $R$-squared | | 13.18% | |
| Wald $\chi^2$ | | 30,715.33 | |
| Obs. | | 408,040 | |

**Notes**: Logistic regression of *CFF* on variables determining the analyst choice to forecast cash flows and control variables. The regression includes an (unreported) constant. Appendix 1 provides variable definitions. We use the output of this regression, the probability of forecasting cash flows, to calculate the propensity score. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

**Table 5**
**Estimation of the effect of cash flow forecast availability on target price accuracy**

| *Dependent variable* *TPerr* | *OLS estimation* (1) | *Propensity score linear mode* (2) | *OLS estimation on the matched sample* (3) |
|---|---|---|---|
| *CFF* | 0.001 | −0.044*** | −0.055*** |
| | [0.832] | [0.000] | [0.000] |
| *Accrual* | 0.139*** | 0.070*** | 0.109*** |
| | [0.000] | [0.000] | [0.000] |
| *AltmanZ* | 0.006*** | 0.006*** | 0.008*** |
| | [0.000] | [0.000] | [0.000] |
| *Capital* | 0.014*** | −0.027*** | −0.046*** |
| | [0.000] | [0.000] | [0.000] |
| *MCap* | −0.114*** | −0.116*** | −0.119*** |
| | [0.000] | [0.000] | [0.000] |
| *EVol* | 0.031*** | 0.026*** | 0.029*** |
| | [0.000] | [0.000] | [0.000] |
| *Freq* | 0.007*** | 0.005*** | 0.001*** |
| | [0.000] | [0.000] | [0.006] |
| *Star* | 0.000 | 0.012*** | 0.017*** |
| | [0.962] | [0.001] | [0.000] |
| *InstOwn* | −0.160*** | −0.154*** | −0.198*** |
| | [0.000] | [0.000] | [0.000] |
| *nAnal* | 0.008*** | 0.005*** | 0.006*** |
| | [0.000] | [0.000] | [0.000] |
| *EPSerr* | 0.716*** | 0.671*** | 0.716*** |
| | [0.000] | [0.000] | [0.000] |
| *StrBuy* | 0.055*** | 0.076*** | 0.088*** |
| | [0.000] | [0.000] | [0.000] |
| *Buy* | 0.033*** | 0.034*** | 0.045*** |
| | [0.000] | [0.000] | [0.000] |
| *Sell* | 0.055*** | 0.101*** | 0.131*** |
| | [0.000] | [0.000] | [0.000] |
| *Lev* | 0.063*** | 0.124*** | 0.119*** |
| | [0.000] | [0.000] | [0.000] |
| Analyst fixed effects | No | Yes | Yes |
| Firm fixed effects | No | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes |
| After Matching | No | Yes | Yes |
| Adjusted *R*-squared | 14.37% | 16.49% | 16.73% |
| *N* | 408,040 | 408,040 | 408,040 |

**Notes**: Column 1 estimates the effect of cash flow forecast availability on target price accuracy using OLS. Column 2 estimates results using a propensity score linear model on the matched sample. Column 3 repeats the estimation of column 1 using OLS on the matched sample. All regressions include an (untabulated) constant. *p*-values are based on standard errors clustered by analyst and firm; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Appendix 1 provides variable definitions.

**Table 6**
**Estimation of the effect of cash flow forecast accuracy on target price error**

| | *TPerr* |
|---|---|
| *CFFerr* | 0.791*** |
| | [0.000] |
| *Accrual* | 0.112*** |
| | [0.000] |
| *AltmanZ* | 0.001 |
| | [0.425] |
| *Capital* | 0.004** |
| | [0.033] |
| *MCap* | -0.093*** |
| | [0.000] |
| *EVol* | 0.009*** |
| | [0.000] |
| *Freq* | 0.006*** |
| | [0.000] |
| *Star* | -0.027** |
| | [0.017] |
| *InstOwn* | -0.059*** |
| | [0.000] |
| *nAnal* | 0.005*** |
| | [0.000] |
| *EPSerr* | 0.364*** |
| | [0.000] |
| *StrBuy* | 0.025*** |
| | [0.000] |
| *Buy* | 0.008 |
| | [0.126] |
| *Sell* | 0.007 |
| | [0.778] |
| *Lev* | 0.151*** |
| | [0.000] |
| Analyst fixed effects | Yes |
| Firm fixed effects | Yes |
| Year fixed effects | Yes |
| Adjusted $R$-squared | 10.3% |
| $N$ | 38,650 |

**Notes**: The table estimates the effect of cash flow forecast error on target price accuracy. The regression includes an (unreported) constant. $p$-values are based on standard errors clustering by analyst and firm; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Appendix 1 provides variable definitions.

**Table 7**
**Estimation of the effect of cash flow forecast availability on target price error based on the same analyst with different firms**

| | *TPerr* |
|---|---|
| *CFF* | −0.070*** |
| | [0.000] |
| *Accrual* | 1.032*** |
| | [0.000] |
| *AltmanZ* | 0.032*** |
| | [0.000] |
| *Capital* | 0.577*** |
| | [0.000] |
| *MCap* | −0.379*** |
| | [0.000] |
| *EVol* | −0.133*** |
| | [0.000] |
| *Freq* | −0.066*** |
| | [0.000] |
| *Star* | 0.136*** |
| | [0.083] |
| *InstOwn* | −0.619*** |
| | [0.000] |
| *nAnal* | −0.023*** |
| | [0.000] |
| *EPSerr* | −0.201*** |
| | [0.000] |
| *StrBuy* | 0.047*** |
| | [0.000] |
| *Buy* | 0.038*** |
| | [0.000] |
| *Sell* | 0.011*** |
| | [0.000] |
| *Lev* | −0.764*** |
| | [0.000] |
| Year fixed effects | Yes |
| Adjusted $R$-squared | 39.6% |
| *N* | 6,756 |

**Notes**: The table reports the results of estimating equation (2) separately for each analyst, for a total of 6,756 regressions. We report the mean coefficients across 6,756 regressions and corresponding $p$-values; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. We also report the average adjusted $R^2$. Appendix 1 provides variable definitions.

**Table 8**
**The effect of cash flow forecast accuracy on target price error for more challenging-to-value firms compared with non-challenging firms**

| | *TPerr* (1) | *TPerr* (2) |
|---|---|---|
| *CFF* | −0.038*** | |
| | [0.000] | |
| *Challanging* | 0.005*** | −0.023*** |
| | [0.008] | [0.001] |
| *CFF* × *Challanging* | −0.020*** | |
| | [0.000] | |
| *CFFerr* | | 0.353*** |
| | | [0.000] |
| *CFFerr* × *Challanging* | | 0.763*** |
| | | [0.000] |
| *Accrual* | 0.069*** | 0.085*** |
| | [0.000] | [0.000] |
| *AltmanZ* | 0.006*** | 0.003*** |
| | [0.000] | [0.006] |
| *Capital* | −0.027*** | −0.036** |
| | [0.000] | [0.028] |
| *MCap* | −0.115*** | −0.097*** |
| | [0.000] | [0.000] |
| *EVol* | 0.026*** | 0.007*** |
| | [0.000] | [0.002] |
| *Freq* | 0.005*** | 0.002 |
| | [0.000] | [0.239] |
| *Star* | 0.012*** | −0.012 |
| | [0.001] | [0.339] |
| *InstOwn* | −0.153*** | −0.087*** |
| | [0.000] | [0.000] |
| *nAnal* | 0.005*** | 0.004*** |
| | [0.000] | [0.000] |
| *EPSerr* | 0.671*** | 0.342*** |
| | [0.000] | [0.000] |
| *StrBuy* | 0.076*** | 0.051*** |
| | [0.000] | [0.000] |
| *Buy* | 0.034*** | 0.018*** |
| | [0.000] | [0.004] |
| *Sell* | 0.101*** | 0.062* |
| | [0.000] | [0.054] |
| *Lev* | 0.124*** | 0.194*** |
| | [0.000] | [0.000] |

| | | |
|---|---|---|
| Analyst fixed effects | Yes | Yes |
| Firm fixed effects | Yes | Yes |
| Year fixed effects | Yes | Yes |
| After matching | Yes | No |
| Adjusted *R*-squared | 11.6% | 10.5% |
| *N* | 48,040 | 38,650 |

**Notes**: The table estimates the effect of cash flow forecast error on target price accuracy, where the dummy variable *Challenging* defines a firm that is more challenging to value based on whether it makes a loss in the year before the analyst forecast announcement, it has a limited number of industry peers in the sample, it is small, or it has high risk. Both regressions include an (unreported) constant. *p*-values are based on standard errors clustered by analyst and firm; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Appendix 1 provides variable definitions.

**Table 9**
**Additional controls and analysis**

| | | | | | | *Sub-periods* | | | *Sub-periods* | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Dependent variable | *Up vs. down markets* | | *Forecast horizon* | *Excluding Energy* | | 2000–2003 | 2004–2006 | 2007–2010 | 2000–2003 | 2004–2006 | 2007–2010 |
| *TPerr* | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) |
| *CFF* | −0.043*** | | | −0.047*** | | 0.078*** | 0.049*** | −0.055*** | | | |
| | [0.000] | | | [0.000] | | [0.000] | [0.000] | [0.000] | | | |
| *CFFerr* | | 0.764*** | 0.769*** | | 0.813*** | | | | −0.219 | 1.141*** | 0.946*** |
| | | [0.000] | [0.000] | | [0.000] | | | | [0.251] | [0.000] | [0.000] |
| Control Covariates | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Additional Control Variables | *Up* | *Up* | *HorizonCF, Horizon* | | | | | | | | |
| Sample | Full Sample | CF Sample | CF Sample | No Energy Sector | No Energy Sector | Years 2000–2003 | Years 2004–2006 | Years 2007–2010 | Years 2000–2003 | Years 2004–2006 | Years 2007–2010 |
| After matching | Yes | No | No | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Analyst fixed effects | Yes | Yes | Yes | Yes | Yes | No | No | No | No | No | No |
| Firm fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted *R*-squared | 12.10% | 11.00% | 10.40% | 11.30% | 7.00% | 8.50% | 2.80% | 9.60% | -5.70% | 1.10% | 8.20% |
| *N* | 408,040 | 38,650 | 38,650 | 336,541 | 24,998 | 100,310 | 103,819 | 203,911 | 3,340 | 9,181 | 26,129 |

Notes: The table presents the results of additional analysis. Column 1 (2) estimates the effect of cash flow forecast availability (cash flow forecast error) on target price accuracy controlling for the effect of up vs. down markets. Column 3 estimates the effect of cash flow forecast error on target price accuracy, controlling for target price and cash flow forecast horizons. Column 4 (5) estimates the effect of cash flow forecast availability (cash flow forecast error) on target price accuracy excluding energy companies. Columns 6–8 (9–11) estimate the effect of cash flow forecast availability (cash flow forecast error) on target price accuracy for the subperiods: 2000–2003, 2004–2006 and 2007–2010. All estimations are performed after matching. *p*-values are based on standard errors clustered by analyst and firm; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Appendix 1 provides variable definitions.

**Appendix 1**
**Variable definitions**

| Variable | Variable name | Definition |
|---|---|---|
| *Accrual* | Magnitude of accruals | The absolute value of net income before extraordinary items minus operating cash flows divided by total assets. |
| *AltmanZ* | Altman's *Z* score | *Z* = 1.2(Net working capital/Total assets) + 1.4(Retained earnings/Total assets) + 3.3(Earnings before interest and taxes/Total assets) + 0.6(Market value of equity/Book value of liabilities) + 1.0(Sales/Total assets). |
| *Buy* | Buy recommendation dummy | Equals one when the analyst stock recommendation is Buy, zero otherwise. |
| *Capital* | Capital intensity | Gross property, plant and equipment divided by revenue. |
| *Challenging* | Challenging firm dummy | Equals 1 if the firm is more challenging to value based on company size, risk, profitability, or number of industry peers, zero otherwise. |
| *CFF* | Cash flow forecast dummy | Equals 1 if the observation includes a cash flow forecast, zero otherwise. |
| *CFFerr* | Cash flow forecast error | The absolute value of the difference between the analyst cash flow forecast minus the actual realized cash flow per share at the end of the forecast period, divided by the share market price at the time of forecast. |
| *EPSerr* | Earnings forecast error | The absolute value of the difference between the analyst earnings per share forecast minus the actual realized earnings per share at the end of the forecast period, divided by the sharemarket price at the time of forecast. |
| *EVol* | Earnings volatility | The natural logarithm of the standard deviation of earnings over the past four quarters, where earnings is total earnings before extraordinary items. |
| *Hold* | Hold recommendation dummy | Equals one when the analyst stock recommendation is Hold, zero otherwise. |
| *InstOwn* | Institutional ownership | Total number of shares held by institutional investors divided by the total number of shares outstanding. |
| *Lev* | Leverage | The company's debt-to-assets ratio for the year. |
| *MCap* | Market capitalization | The natural logarithm of the company's equity market value. |
| *nAnal* | Number of analysts following | The I/B/E/S number of analysts following the company in the year. |
| *Freq* | Forecast frequency | The number of target price revisions issued by a given analyst for the company in the year. |
| *Sell* | Sell recommendation dummy | Equals one when the analyst stock recommendation is Sell, zero otherwise. |
| *Star* | Star analyst dummy | Equals one if the analyst is an Institutional Investor star analyst in the year before the release of the current analyst forecast, zero otherwise. |
| *StrBuy* | Strong buy recommendation dummy | Equals one if the analyst stock recommendation is Strong Buy, zero otherwise. |

| | | |
|---|---|---|
| *TPerr* | Target price forecast error | The absolute value of the difference between the target price and the market price at the end of the forecast horizon divided by the current market price. |