Analyst target price accuracy and the incidence of cash flow forecasts

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February 2015

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ABSTRACT

Research shows that analyst target price accuracy is limited and yet evidence on the factors driving this limited accuracy is inconclusive. Complementing the results of recent studies that show that the increasing incidence of cash flow forecasts in analyst reports has helped mitigate accruals mispricing, we address the question: are analyst target prices more accurate when accompanied by cash flow forecasts than when they are not? Using propensity score matching to control for selection bias, we estimate the effect of disclosing cash flow forecasts on the target price accuracy of US stocks during 2000–2010. The results suggest that target prices are more accurate when analysts also disclose cash flow forecasts. The paper contributes to the continuing debate about the usefulness of analyst target prices as well as the usefulness of analyst cash flow forecasts.

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

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

1. Introduction

Analysts are increasingly augmenting their equity reports, which include earnings forecasts as standard, with target price and cash flow forecasts. Unlike a stock recommendation, a target price gives investors an implicit estimate of the expected stock return over the forecast horizon, which can aid them in their investment decisions. In the analyst literature, however, some authors question the usefulness of target prices for capital market participants. More specifically, there is an unsettled debate on the limited accuracy of analyst target prices. At the same time, recent studies emphasize that analyst target prices are generally under-researched (e.g., Bradshaw, 2011; Bradshaw et al., 2012). We contribute to this literature by examining the unresearched question of whether cash flow forecasts improve the accuracy of analyst target prices.

Previous research examines some of the factors that influence target price accuracy, including analyst optimism (Asquith et al. 2005), the number of reports published by the analyst (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 to the accuracy of their earnings forecasts. In a sample of 818 target prices issued during 1997–1999 by *Institutional Investor*'s star analysts, 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 a sample of 1,000 German stocks during 2002–2004. Bonini et al. (2010) find an accuracy of 33.1% for a sample of 10,939 target prices issued during 2000–2006 for 98 Italian stocks. For a large sample of 492,647 target prices for US stocks during 2000–2009, Bradshaw et al. (2012) report an accuracy of 64% and a prediction error of 45%.

The literature does not offer 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, De Vincentiis 2010, Kerl 2011), suggesting that analyst optimism reduces accuracy. On the other hand, De Vincentiis (2010) and 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 issued by an analyst 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 significant supporting evidence. De Vincentiis (2010), however, shows that the number of firms the analyst covers and analyst company-specific experience improve target price accuracy. Demirakos et al. (2010) present evidence of analyst ability to make intelligent valuation model choices. Their evidence suggests that analysts select a valuation model that is appropriate to the difficulty of the valuation task and that accuracy does not vary with valuation model choice after accounting for this.

The literature also examines factors relating to company risk. 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). Bonini et al. (2010) find that momentum and loss making firms are associated with higher forecast errors. Stock price volatility reduces accuracy according to Demirakos et al. (2010), De Vincentiis (2010), and Kerl (2011). Information uncertainty is also likely to influence analyst behavior. 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. 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.

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). In this study, we examine whether the disclosure of cash flow forecasts by an analyst improves the analyst's target price accuracy. Analyst began including cash flow forecasts in their equity reports relatively recently. On the Institutional Brokers' Estimate System (I/B/E/S), cash flow forecasts started appearing alongside earnings forecasts in 1993, although in the early years only a few reports included them. 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) and to 32 percent in 2005 (Call et al., 2009). Asquith et al. (2005) provide a detailed description of the typical analyst report based on a content analysis of 1,126 equity reports (of which 72.6 percent include target prices) issued by *Institutional Investor*'s All-American Research Team between 1997 and 1999. They find that 17.1 percent disclose cash flow forecasts, comparable to the findings of DeFond and Hung (2003).

Although several researchers have examined the role and properties of cash flow forecasts,[4] Mangen (2013) observes that this research is still in its infancy. Recent literature suggests that issuing cash flow forecasts is not a random decision, nor a simple time trend. DeFond and Hung (2003) study the determinants of the selective supply of cash flow forecasts and attribute it to market participants' demand. They find that the

[4] See, for example, Govindarajan (1980), Defond and Hung (2003), Hodder et al. (2008), Call et al. (2009), Givoly et al. (2009), McInnis and Collins (2011), and Pae and Yoon (2012).

decision to issue cash flow forecasts depends on firm-specific factors, primarily proxies for uncertainty facing the 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. Lehavy (2009), however, argues that their response-to-investor-demand explanation is questionable given Givoly et al.'s (2009) evidence that analysts' cash flow forecasts are unsophisticated.

Givoly et al. (2009) argue that cash flow forecasts are 'naïve extensions' of earnings forecasts and can be derived by adding back depreciation and working capital changes to earnings. They also question the usefulness of cash flow forecasts given their low accuracy compared with earnings forecasts. Challenging this, Call et al. (2009) show that disclosing cash flow forecasts improves the accuracy of analysts' earnings forecasts. Lehavy (2009), commenting on the contradictory findings, highlights robustness concerns in support of the view that cash flow forecasts are unsophisticated. Call et. al. (2013a) investigate the accruals adjustments that analysts make to forecast their cash flows and provide evidence on the sophistication of these forecasts. They show that analysts incorporate meaningful estimates of working capital and other accruals to reconcile earnings to cash flow forecasts. Further, they find a significant market reaction to analyst cash flow forecast revisions incremental to the reaction to earnings forecast revisions. Givoly et al. (2013) argue that Call et al.'s (2013a) results are 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 suggests that the usefulness of analysts' cash flow forecasts is contentious and the question of their sophistication is open to judgement (Call et al., 2013b). Recent studies by Mohanram (2014) and Radhakrishnan and Wu (2014), however, show how the increasing incidence of cash flow forecasts has helped mitigate accruals mispricing. Their results suggest that the presence of analysts' cash flow forecasts for a firm enable investors to price that firm more accurately. We complement this research by examining whether an analyst improves the accuracy of her target price when she also discloses a cash flow forecast. Using propensity score matching (PSM), we analyze the performance of analyst target prices accompanied by cash flow forecasts during 2000–2010. The analysis shows that an analyst's target price accuracy improves when the analyst accompanies this with a cash flow forecast.

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 determinants of analyst target price accuracy and to add to our understanding of the properties of analyst target prices. Our findings shed light on the value and sophistication of analyst cash flow forecasts. Understanding the value of cash flow forecasts for target price valuation is relevant to investors. Demirakos et al. (2010) report that the choice of discounted cash flow (DCF) or price-to-earnings (PE) valuation models does not affect the quality of analyst target prices after controlling for the difficulty of the valuation task. Moreover, the current evidence on how the quality of valuation inputs affects valuation outcomes is based only on earnings forecasts. For a sample of 45,693 target prices during 1997 through 2003, 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 analyst target prices and the difference in profitability between the two valuations. By testing how cash flow forecasts affect analyst valuations, we offer insights into the analyst ‘black box’ that researchers attempt to penetrate.

2. Research hypotheses

Research shows that cash flows and accounting earnings are each incrementally useful in assessing firm value (e.g., Bowen et al., 1987; Ali, 1994; Dechow, 1994). In the analyst literature, Gleason et al. (2013) find that the profitability of target prices deteriorates when using low quality earnings forecasts as valuation inputs. 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 forecasts and the quality of these forecasts on target price accuracy.

Recent findings by Mohanram (2014) suggest 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, should help reduce the mispricing. Radhakrishnan and Wu (2014) provide support for these findings.

Complementing this research, we examine the benefit to the analyst of providing a cash flow forecast in terms of the effect on the accuracy of target prices. We hypothesize that an analyst’s target price accuracy is higher if the analyst also provides a cash flow forecast. Our hypothesis assumes that the quality of valuation model inputs affects the reliability of the valuation process. It is also based on the finding that the presence of cash flow forecasts increases the quality of analyst earnings forecasts, which is another key input to analyst valuations. We therefore expect the presence of cash flow forecasts to improve the quality of analyst valuations. This leads to our first hypothesis:

H1: *An analyst's target price is more accurate if the analyst also provides a cash flow forecast.*

We next hypothesize that the increase in target price accuracy is stronger when cash flow forecasts are more accurate. Given the evidence of Givoly et al. (2009) that analyst cash flow forecasts are not useful to market participants because of their low quality, it is possible that cash flow forecasts as a valuation model input introduce additional bias to analyst target prices. However, if analyst cash flow forecasts are accurate, they should result in higher target price quality. We therefore differentiate between accurate and inaccurate cash flow forecasts and their effects on target price accuracy. We test the following second hypothesis:

H2: *An analyst's target price accuracy increases with the accuracy of the analyst's cash flow forecast.*

3. Data and sample

We obtain one-year-ahead cash flow forecasts for US stocks from the I/B/E/S detail file. We focus on one-year forecasts because cash flow forecasts on I/B/E/S are mostly annual. We merge these with target prices from the I/B/E/S target price file based on company ticker, estimator ID, analyst mask code, and announcement date. For each observation, 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 forecast horizon divided by the current market price.[5] Observations that have a target price (TP) and a cash flow forecast (CFF) belong to the CFF group, while observations that have only TP

[5] 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; De Vincentiis, 2010). We follow Demirakos et al. (2010) in calculating our (inverse) accuracy measure.

belong to the no-CFF group. A check of the dataset shows that no analyst–company pairs in the no-CFF group have any cash flow forecast observations by the same analyst for the same company at a different date in the dataset. This eliminates any ambiguity regarding observations in the no-CFF group. We obtain the target price consensus forecast, used in some of the analyses below, from the I/B/E/S summary file. Return data are from CRSP. Financial statement information and footnote data are from Compustat.

Table 1 shows the final sample distribution. The sample covers January 2000 to December 2010 and includes 4,387 firms in 48 industries (according to the Fama and French, 1997, industry classification), 7,114 security analysts, and 597 research departments. The sample size is 420,813 observations. The number of observations including a CFF is 43,044, comprising about 10 percent of the sample. The observations with a CFF cover 2,057 firms for 1,755 analysts working for 270 research departments. The percentage of CFF observations in the sample increases from 4 percent in 2000 to almost 15 percent in 2010.[6]

4. Research design

We want to measure the impact of a 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 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

[6] The percentage of CFF observations is lower than in previous literature because we require our sample observations to include a target price forecast.

differences between groups. We then run a multivariate regression on the matched sample to achieve higher efficiency and double filtering. 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 company–analyst observation includes a CFF using the following logistic regression,

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

The propensity score model estimates the conditional probability of a CFF given observable features of analysts and the company. *CFF* is a dummy variable that indicates whether observation *i* includes a CFF. 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. Large accruals increase market suspicion, making cash flow information valuable for interpreting the information in earnings. Altman’s *Z*-score (*AltmanZ*) measures a company’s financial health, where lower *Z*-scores indicate worse financial health (Altman, 1968). Cash flow forecasts should be more important for assessing the value of companies in worse financial health. Capital intensity (*Capital*) is the level of fixed assets in the company. When capital intensity is high, cash flow information is useful for assessing a firm’s liquidity. The natural logarithm of the company’s equity market value (*MCap*) controls for the company’s information environment. Earnings volatility (*EVol*) captures earnings quality. According to DeFond and Hung (2003), analysts are more likely to issue cash flow forecasts for firms with larger absolute accruals, high capital intensity, low *Z*-scores, and high earnings volatility.

The second set of explanatory variables controls for analyst characteristics. Evidence in Ertimur and Stubben (2005) suggests that analyst characteristics can influence their incentives to forecast cash flows. We therefore 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*). We include stock recommendation categories (*StrongBuy*, *Buy*, *Sell*) to control for the sensitivity of target price accuracy to analyst recommendations. We also include leverage (*Lev*) to control for a company's financial performance.[7]

Table 3 provides summary statistics for the variables in the model for the full sample and for the treatment and control groups of CFF and no-CFF observations, as well as the results of mean and median differences tests between the two samples. The significant differences in means and medians between the two groups call for controlling using matching methods. The summary statistics for all variables in the model raise no particular concerns for the implementation of the propensity score analysis.

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, controlling for analyst fixed effects,

$$\begin{aligned} &TPerr_i = \\ &\beta_0 + \beta_1 CFF + \beta_2 Accruals_i + \beta_3 AltmanZ_i + \beta_4 Buy_i + \beta_5 Capital_i + \beta_6 EVol_i \\ &+\beta_7 Freq_i + \beta_8 InstOwn_i + \beta_9 Lev_i + \beta_{10} MCap_i + \beta_{11} nAnal_i + \beta_{12} Sell_i \\ &+\beta_{13} Star_i + \beta_{14} StrBuy_i + u_i \end{aligned} \tag{2}$$

The dependent variable is our measure of inverse target price accuracy (*TPerr*). The parameter of main interest in this model is β_1; if target price observations with cash flow forecasts are more accurate, we expect to observe a negative coefficient on the *CFF*

[7] Table 2 provides precise definitions of all the study variables in the main analysis.

dummy. A negative coefficient suggests that target price error is lower for observations that have analyst cash flow forecasts, compared with the target price error of observations with no cash flow forecasts.

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.

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

We estimate the cash flow forecast error *CFFerr* (inverse accuracy) as the absolute value of the difference between the cash flow forecast and the actual cash flow per share as reported by the IBES Detail History – Actuals file for the relevant end of forecast period, divided by the stock price at the time of the forecast. If target prices are more accurate when analysts make more accurate cash flow forecasts, we should observe a positive coefficient on the cash flow forecast error. This would suggest that lower cash flow forecast errors lead to lower target price errors.

5. Empirical estimation and results

We first conduct a univariate analysis of the differences in firm characteristics between observations with and without cash flow forecasts. Table 4, panel A compares the magnitude of accruals, *Z*-score, capital intensity, earnings volatility, institutional ownership, leverage, market capitalization, number of analysts following, and target price error for the two groups. On average, analysts issue cash flow forecasts for companies with larger absolute accruals, lower *Z*-scores, higher capital intensity, higher earnings volatility, and larger market capitalization, consistent with previous findings in the literature. We also find that companies with cash flow forecasts have a larger analyst following and higher levels of leverage and institutional ownership, on average. Moreover, target price accuracy is higher for companies with cash flow forecasts. These significant differences support our argument that the analyst decision to forecast cash flows is not random. According to the correlation matrix of the variables (not tabulated), there is a high correlation of 0.68 between company size and analyst following as expected. The correlations between other variables do not raise any concerns of multicollinearity for the regression analysis. Multicollinearity is not an issue for the propensity score matching estimation because estimating the effects of individual covariates is not the 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 25th percentile of *CFFerr* as observations with low cash flow forecast error and observations above the 75th percentile as observations with high cash flow forecast error. Table 4, panel B presents the differences in mean and median between the two groups. The average target price error is 0.560 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 target price accuracy is likely to be 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 4, panel B shows that observations with above average CFF error have a mean target price error of 0.548 while observations with below average CFF error have a mean target price error of 0.417. Differenced in means and median between the two groups are significant.

Table 5 reports the results of the logistic regression estimation of equation (1). Consistent with DeFond and Hung (2003) and our univariate analysis, Altman's Z-score is negatively associated with the analyst decision to disclose a CFF, while absolute accruals, earnings volatility, capital intensity, and size are positively associated with CFF disclosure. This suggests that analysts disclose cash flow forecasts for firms with weaker financial health, 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 level of institutional ownership and companies that are followed by a larger number of analysts (i.e., more visible firms). Analysts are more likely to provide cash flow forecasts for companies they cover for more frequently. There is a negative association between analyst star ranking and the incidence of 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 there are factors that call for improving for their earnings forecasts. If non-Star analysts are more likely to make earnings forecasts that are of a lower quality then they have more incentive to supplement their earnings with cash flow forecasts.

We use the results of the logistic regression to estimate the propensity score for each observation in the 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.[8] 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

[8] 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.

most of the covariates; most *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 the 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.

Table 6 reports the results of estimating equation 2 to test our first hypothesis of the association between cash flow forecast availability and target price accuracy. For comparison purposes, we report the results of OLS estimation without any matching or control for selection bias in column 1. The results show a negative association between cash flow availability and target price error. This implies that the presence of a cash flow forecast reduces the target price forecast error. The coefficients on the other covariates in the estimation suggest that target price error falls for firms with more institutional ownerships holdings and for larger companies. On the other hand, target price error is higher for Star analysts and when the analyst provides higher coverage for a particular company. Moreover, target price error increases for companies with more volatile and uncertain earnings and companies with a larger analyst following.

Next, we use the matched sample from the propensity score estimation and combine it with various regression adjustments. Columns 2–4 report the estimation of the model after matching. Combining regression with matching involves running the chosen regression model (e.g., the generalized linear model in column 2) with the matched observations from the CFF and no-CFF groups and the propensity scores included as covariates in the regression. This regression-adjusted matching can protect against bias from model misspecification.[9] Column 2 estimates the effect on target price accuracy using maximum likelihood estimation of a generalized linear regression model with a gamma distribution and a log link over the matched sample. The advantage of this approach is that it provides a more flexible approach that has the potential to address nonlinear relationships between covariates and the outcome variable. The generalized linear model analyzes the linear relationship between the explanatory variables and the mean of the dependent variable even when it is not reasonable to assume the data is distributed normally. Target price error falls in the presence of cash flow forecasts with *CFF* having a coefficient of −0.053 (p=0.000). The results on other covariates suggest target price error is lower for higher capital intensity, higher institutional ownership, and larger market capitalization.

Column 3 estimates results using a propensity score linear model controlling for analyst fixed effects over the matched sample. Column 4 repeats the estimation of column 1 using OLS over the matched sample. The results in columns 3 and 4 are consistent with the GLM estimation. The coefficients on *CFF* are −0.058 and −0.071, both significant at p=0.000. Moreover, the results of the estimation after matching are consistent with the results of the OLS regression. 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.

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 38,848 observations because not all observations contain a cash flow

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

forecast and for some cash flow forecasts IBES does not report an actual cash flow for the forecast period end date, which we need to calculate the cash flow forecast error for each observation. Table 7, column 1 presents the results of the estimation. Consistent with our prediction, the coefficient on *CFFerr* of 1.1 suggests that analyst target prices accompanied by more accurate cash flow forecasts are more accurate. Table 7, column 2 repeats the estimation, 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 column 1, suggesting that observations with above average cash flow forecast errors have higher target price forecast errors.

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 6, column 3, changing CFF from zero to one reduces the mean target price error by 12.34%. Second, a one standard deviation change in *CFFerr* reduces the target price error by 581.67 basis points and the mean target price error by 10.66%.

6. Additional analysis

We undertake several sensitivity tests and report the results in the text. 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. We also test the sensitivity of our results to controlling for temporal effects and for previous findings that cash flow forecast accuracy declines over time. We add time fixed effects to our models and 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. Our results are not affected by these additional controls and both *HorizonCF and HorizonTP* do not have significant coefficients in most regressions after controlling for time fixed effects.

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 5 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 our two hypothesis tests are affected by removing observations from the Energy sector to check if this industry drives our results. Doing this does not change the results we report in the main analysis.

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 all coefficients on *CFF* and *CFFerr* having the same sign and significance as the estimation on the full sample. This suggests that our results are not driven by changes occurring over time.

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 company 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 company. We add the control variable *Other-CFF*, which takes the value 1 if a company 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 offer cash flow forecasts benefit from the availability of cash flow forecasts by other analysts. 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 remain significant after matching and have the expected sign and magnitude. The control *Other-CFF* has a negative and significant coefficient, indicating that the availability of cash flow forecasts by other analysts provides additional improvement in analyst target price accuracy.

7. Conclusion

Bradshaw (2011) highlights the need for more research on the analysis that financial analysts undertake. While analysts' decision processes and how they perform their analysis and estimate target prices are unobservable, our study meets this need by exploring the effect of analyst valuation input quality on target prices. We investigate whether analyst target prices are more accurate when analysts make cash flow forecasts than when they do not. 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.

Additionally, we conjecture 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.

Our study contributes to the literature on analyst target prices and cash flows. 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 analyst stock valuations are affected by the quality of the valuation model inputs is of interest to a broad audience of investors, companies, researchers, and analysts.

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Table 1
Sample distribution

	Full Sample	CFF observations	No-CFF observations
Companies	4,387	2,057	4,368
Analysts	7,114	1,755	6,962
Research departments	597	270	586

Year	Full sample	CFF observations	No-CFF observations
2000	20,489	918	19,571
2001	25,425	578	24,847
2002	30,472	846	29,626
2003	31,854	2,361	29,493
2004	34,647	3,461	31,186
2005	34,815	4,043	30,772
2006	37,527	3,896	33,631
2007	40,696	4,315	36,381
2008	52,074	6,625	45,449
2009	53,281	7,537	45,744
2010	59,533	8,464	51,069
Total	420,813	43,044	377,769

Notes:
The table presents the sample distribution by cash flow forecast availability group for companies, analysts, and research departments. The lower part of the table gives the sample observations by year.

Table 2
Variable definitions

Variable	Variable name	Definition
Accruals	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.
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.
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.

Table 3
Descriptive Statistics

Variable	Mean	Std. Dev.	Min	25th	Median	75th	Max
Accruals	0.08	0.13	0.00	0.03	0.06	0.10	11.45
*AltmanZ**	5.80	6.57	−2.74	2.19	3.85	6.74	39.07
Buy	0.34	0.47	0.00	0.00	0.00	1.00	1.00
*Capital**	0.94	1.36	0.00	0.23	0.41	0.9	7.88
*CFFerr**	0.03	0.05	0.00	0.01	0.02	0.04	0.35
CFF	0.10	0.30	0.00	0.00	0.00	0.00	1.00
EVol	2.63	1.84	−4.73	1.30	2.54	3.88	11.12
Freq	4.22	2.63	1.00	2.00	4.00	5.00	33.00
Hold	0.32	0.47	0.00	0.00	0.00	1.00	1.00
InstOwn	0.70	0.22	0.00	0.59	0.75	0.87	1.00
Lev	0.21	0.21	0.00	0.02	0.18	0.32	4.99
MCap	14.69	1.72	7.14	13.47	14.6	15.86	20.14
nAnal	13.19	7.97	1.00	7.00	12.00	18.00	53.00
Sell	0.01	0.12	0.00	0.00	0.00	0.00	1.00
Star	0.17	0.38	0.00	0.00	0.00	0.00	1.00
StrBuy	0.26	0.44	0.00	0.00	0.00	1.00	1.00
*TPerr**	0.47	0.55	0.01	0.15	0.34	0.63	11.00

Notes:
Summary statistics for all variables in the study based on 420,813 observations. *CFFerr* summary statistics are based on 38,848 observations. Asterisked variables are winsorized at the upper and lower 1% levels to reduce outlier effects. Table 2 gives variable definitions.

Table 4
Panel A: Comparison of firm characteristics

	Mean		Median		Mean difference	Median difference
	CFF	No-CFF	CFF	No-CFF	*t*-stat	*z*-stat
Accruals	0.10	0.08	0.07	0.06	−22.498	−44.268
*AltmanZ**	3.96	6.00	2.78	3.99	61.337	78.300
*Capital**	2.13	0.80	1.09	0.39	−200.000	−134.019
EVol	3.13	2.57	3.08	2.48	−60.329	−58.969
InstOwn	0.73	0.70	0.77	0.75	−24.370	−23.738
Lev	0.24	0.21	0.23	0.18	−33.203	−48.410
MCap	15.01	14.65	14.99	14.55	−40.885	−45.179
nAnal	15.39	12.94	14.00	12.00	−60.640	−61.916
*TPerr**	0.45	0.47	0.33	0.34	7.608	4.732

Panel B: Comparison of target price accuracy relative to cash flow forecast accuracy

	Mean		Median		Mean difference	Median difference
	High *CFFerr*	Low *CFFerr*	High *CFFerr*	Low *CFFerr*	*t*-stat	*z*-stat
Obs.	9,712	9,712				
*TPerr**	0.560	0.413	0.379	0.316	−19.072	−14.398
	Above average *CFFerr*	Below average *CFFerr*	Above average *CFFerr*	Below average *CFFerr*	*t*-stat	*z*-stat
Obs.	11,068	27,780				
*TPerr**	0.548	0.417	0.374	0.313	−24.81	−16.911

Notes:
Panel A: A comparison of the characteristics of companies covered by observations with and without cash flow forecasts, giving the means of firm characteristics and the results of mean and median differences tests. The full sample includes 420,813 observations. The numbers of CFF observations and no-CFF observations are 43,813 and 377,769. Table 2 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.
Asterisked variables are winsorized at the upper and lower 1% levels to reduce outlier effects.

Table 5
Propensity-score estimation using logistic regression

Dependent variable	*CFF*
Accruals	0.188***
	[0.000]
AltmanZ	−0.043***
	[0.000]
Buy	−0.119***
	[0.000]
Capital	0.443***
	[0.000]
EVol	0.024***
	[0.000]
Freq	0.055***
	[0.000]
InstOwn	0.783***
	[0.000]
Lev	−0.779***
	[0.000]
MCap	0.050***
	[0.000]
nAnal	0.015***
	[0.000]
Sell	−0.608***
	[0.000]
Star	−0.221***
	[0.000]
StrBuy	−0.292***
	[0.000]
Constant	−4.059***
	[0.000]
Pseudo R-squared	11.59%
Wald χ^2	28138.1
	[0.000]
Obs.	420,813

Notes: Logistic regression of *CFF* on the variables determining analyst choice to forecast cash flows and control variables. The output of this regression, the probability of forecasting cash flows, is used to calculate the propensity score. Table 2 provides variable definitions.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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

TPerr	1	2	3	4
CFF	−0.019***	−0.053***	−0.058***	−0.071***
	(−3.31)	(−7.75)	(−12.85)	(−15.72)
Accruals	0.135***	0.152***	0.077***	0.125***
	(5.34)	(12.51)	(11.98)	(7.09)
AltmanZ	0.009***	0.019***	0.009***	0.013***
	(23.69)	(46.64)	(37.43)	(32.90)
Buy	0.040***	0.103***	0.038***	0.057***
	(11.07)	(27.76)	(17.62)	(25.27)
Capital	0.016***	−0.024***	−0.017***	−0.041***
	(7.68)	(−3.88)	(−4.68)	(−7.78)
EVol	0.043***	0.064***	0.036***	0.040***
	(23.71)	(51.05)	(47.45)	(40.51)
Freq	0.005***	0.008***	0.004***	−0.002***
	(6.36)	(8.53)	(7.05)	(−3.22)
InstOwn	−0.233***	−0.408***	−0.220***	−0.311***
	(−24.56)	(−40.61)	(−37.25)	(−37.80)
Lev	0.153***	0.314***	0.205***	0.226***
	(14.21)	(28.40)	(32.12)	(24.61)
MCap	−0.133***	−0.248***	−0.135***	−0.138***
	(−53.58)	(−167.37)	(−142.88)	(−94.33)
nAnal	0.007***	0.013***	0.005***	0.006***
	(22.45)	(43.46)	(25.85)	(29.65)
Sell	0.044***	0.202***	0.087***	0.114***
	(3.61)	(14.41)	(11.04)	(12.01)
Star	0.032***	0.074***	0.052***	0.058***
	(5.32)	(16.01)	(13.40)	(18.98)
StrBuy	0.059***	0.162***	0.080***	0.098***
	(13.84)	(31.08)	(25.93)	(25.86)
Constant	2.210***	2.378***	2.211***	2.259***
	(66.73)	(126.77)	(181.98)	(114.44)
After Matching	No	Yes	Yes	Yes
R-squared	10.7%		10.5%	10.8%
Log likelihood	−79240.72			
N	420,813	420,813	420,813	420,813

Notes: Column 1 estimates the effect of cash flow forecast availability on target price accuracy using OLS. Column 2 estimates the effect on target price accuracy using maximum likelihood estimation of a generalized linear model on the matched sample. Column 3 estimates results using a propensity score linear model controlling for analyst fixed effects on the matched sample. Column 4 repeats the estimation of column 1 using OLS on the matched sample. *t*-stats are based on standard errors adjusted for clustering by analysts and companies to adjust for within cluster correlation. Table 2 provides variable definitions.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7
Estimation of the effect of cash flow forecast accuracy on target price accuracy

	1	2
CFFerr	1.100***	
	(22.18)	
Above average CFFerr		0.039***
		(7.13)
Accruals	0.060***	0.047**
	(3.17)	(2.47)
AltmanZ	0.002***	0.002***
	(3.39)	(2.86)
Buy	0.009*	0.008
	(1.68)	(1.34)
Capital	−0.002	−0.003*
	(−0.95)	(−1.66)
EVol	0.002	0.009***
	(0.95)	(4.29)
Freq	0.010***	0.010***
	(9.79)	(10.27)
InstOwn	−0.027**	−0.044***
	(−2.14)	(−3.44)
Lev	0.222***	0.242***
	(12.84)	(13.94)
MCap	−0.087***	−0.103***
	(−29.34)	(−35.13)
nAnal	0.003***	0.003***
	(6.06)	(7.18)
Sell	0.006	0.01
	(0.23)	(0.38)
Star	0.047***	0.049***
	(4.14)	(4.31)
StrBuy	0.013*	0.012*
	(1.84)	(1.67)
Constant	1.576***	1.819***
	(37.41)	(43.96)
Analyst fixed effects	Yes	Yes
R-squared	12.62%	12.71%
N	38,848	38,848

Notes: Column 1 estimates the effect of cash flow forecast error on target price accuracy using a fixed effects regression. Column 2 estimates the effect of above average *CFFerr* on target price accuracy. *t*-stats are based standard errors adjusted for clustering by analysts and companies to adjust for within cluster correlation. Table 2 provides variable definitions.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$