Do formal risk assessments improve analysts' target price accuracy?*

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ABSTRACT

Equity analysts' target price estimates are uncertain. Some analysts gauge this uncertainty by supplementing their target prices with a risk assessment in the form of a bull–bear analysis (BBA). We explore whether disclosing a BBA reduces analysts' target price error or, alternatively, whether analysts disclose a BBA to make their forecasts seem more credible and distract attention from less accurate target prices. Using propensity score matching to control for selection bias, combined with a difference-in-differences estimation to allow for company- and analyst-specific effects, we estimate the effect of supplementing target prices with a BBA on the target price accuracy of US stocks. We find that target prices are significantly more accurate, both statistically and economically, when analysts supplement them with a BBA. Our results shed light on the role of risk and uncertainty assessments in improving analyst valuations.

JEL classification: M41, G10, G24, G29, C15, C40.

Keywords: bull–bear analysis, equity analysts, information uncertainty, risk assessment, scenario analysis, target price accuracy, valuation.

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1. Introduction

Equity analysts face conflicting incentives that influence their decision making. Research shows that analyst target price accuracy is limited and attributes this to a lack of analysts' incentives to improve their accuracy. This has resulted in an on-going debate about the usefulness of target prices. Asquith et al. (2005) examine 818 target prices issued during 1997–1999 by members of *Institutional Investor's* All-American Research Team achieving at least one First Team ranking and find that 54.3% of target prices are accurate in the sense that the stock price equals or exceeds the target price at some time during the ensuing twelve months. Examining 1,000 analyst reports on German stocks during 2002–2004, Kerl (2011) finds a target price accuracy of 56.5%. For 10,939 target prices during 2000–2006 for 98 companies listed on the Milan Stock Exchange, Bonini et al. (2010) report an accuracy of 33.1%. They also report average target price errors of 37% for strong buy recommendations, 21% for buy recommendations, falling to 10% for hold recommendations and 7% for sell recommendations, and rising to 29% for strong sell recommendations. Bradshaw et al. (2012) find an accuracy of 64% and an error of 45% for 492,647 target prices for US stocks during 2000–2009.

Research also studies the factors that influence target price accuracy, including analyst optimism (Asquith et al., 2005), the number of reports published by an 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). A previously unstudied factor is the uncertainty of analyst forecasts (Pope, 2003). We examine the effect of assessing and incorporating investment risk and uncertainty into analysts' valuations via a bull-bear analysis (BBA) on the accuracy of their target prices.

Analysts use alternative valuation models to generate their target prices, the most popular being price-earnings multiples and the discounted cash flow model. The choice depends on company characteristics and analyst preferences (Demirakos et al., 2010). The inputs to these valuation models necessarily affect target prices, so information uncertainty surrounding these inputs affects target price accuracy.[1] In setting target prices, therefore, analysts have to make assumptions, explicitly or implicitly, about risk. One way in which they incorporate this into their reports is by supplementing their target price with an explicit risk assessment in the form

[1] Zhang (2006a) finds that higher information uncertainty generally leads to higher analyst earnings forecast errors.

of a BBA. In a BBA, analysts assess the effect of alternative scenarios on target prices, by changing valuation model inputs in at least two scenarios, usually upside- and downside-cases. They consider the earnings, cash flows, dividends, and discount rate of the company under best and worst case scenarios, assign probabilities to each scenario, and calculate the target price as the expected value.[2] A BBA can improve the assessment and presentation of investment uncertainty, by recognizing a stock's upside potential and downside risk.

When analysts include a BBA in their reports, they produce two outputs, commonly named bull and bear case target prices, to support the target price highlighted in their report summary. Combined with the stock price, the target price along with the bull and bear target prices imply not only the analyst's estimate of the future expected stock return but also an investment risk assessment (Damodaran, 2010). The bull–bear range scaled by the stock price at the time of announcement should be higher for riskier investments. Joos et al., (2012) use a variant of this metric, which they refer to as the 'spread', to proxy for analyst uncertainty about firms' fundamental values. By examining the association between the bull–bear spread and company-specific risk factors and between the spread and target price error, they show that analysts' scenario-based valuation estimates reflect and convey information about the risks and return potential affecting firm valuations. This suggests that a BBA can improve an analyst's understanding of company risk. We find that analysts' reports often include words to the effect that 'our bull/bear analysis indicates a favorable risk/reward' implying that bull and bear target prices convey information for risk assessment.

A BBA may therefore be a useful risk assessment tool for valuing companies. It can help investors envision possible future states of the world and raise their awareness of a stock's upside and downside potential. While it does not replace expected cash flows or earnings with certainty equivalents, a BBA remedies a shortcoming of traditional valuation by accounting for the uncertainty of analyst valuations. Analysts can use a BBA to compensate for weak valuation model assumptions or estimates or to compensate for an unpredictable future (Thomas, 2001). A BBA can therefore improve the quality of analyst valuations, enhancing risk assessments and the results of valuations, in the form of more accurate target prices.

On the other hand, a BBA may disguise the underperformance of aggressive analysts. More accurate target prices are not an automatic outcome of disclosing a BBA. Analysts may report a BBA to compensate for a less accurate target price, allowing them to argue that the actual price falls in the bull–bear range. Reporting a BBA may make it easier for analysts to

[2] Some analyst reports formally assign probabilities to each scenario and compute the target price as the expected value across scenarios. Other reports indicate a base case target price without formally assigning probabilities.

bias their target prices to generate investment commissions. Disclosing a BBA may placate investors when the target price is biased upwards to curry favour with a company.

Given the increasing popularity of target prices, a natural question to ask is whether a BBA improves the quality of analyst target prices. We answer this question by examining how including a BBA affects target price accuracy, where target price accuracy measures the ability of target prices to predict future stock prices.

Using propensity score matching (PSM) combined with difference-in-differences (DD), we analyze the performance of analyst target prices supported by a BBA. PSM combined with DD allows us to compare the target price accuracy of BBA and non-BBA reports controlling for unobserved effects. This analysis shows that analysts are more likely to supplement target prices with a BBA when they face higher information uncertainty in terms of company age, stock liquidity, and company size, and higher company risk indicated by a negative return on assets and higher leverage. The analysis also shows that analysts are more likely to provide a BBA when they have affiliation-related incentives, but are less likely to provide a BBA when their forecasts are bold or in the presence of high institutional ownership. The DD matching estimation shows that target prices are more accurate when analysts supplement them with a BBA, with the estimated counterfactual target price error in the absence of a BBA being 23.7 percent higher.

There are two broader motivations for studying the impact of a BBA on target price accuracy. First, Pope (2003) suggests there are four fundamental determinants of analyst forecast quality: information, predictability, skill, and incentives. Information refers to the quality of valuation model inputs, while predictability captures fundamental uncertainty in the forecast output. Skill captures analyst forecasting ability and incentives reflect the conflicts of interest arising from analysts' competing roles. Pope (2003, p. 277) argues that 'forecast quality cannot be defined or measured independently of characteristics of predictability.' The literature on target price quality studies factors relating to analyst skills and incentives but neglects the impact of the quality of analyst forecasting inputs and the uncertainty of the valuation outcome. Our study fills this gap by investigating how assessing and incorporating investment risk and uncertainty into analysts' valuation models affects the quality of their target prices. Second, Regulation Fair Disclosure (Reg FD), introduced by the Securities and Exchange Commission in October 2000, banned U.S. companies from making selective, private disclosures to analysts. Previously, analysts depended heavily on access to management as their main source of information (Lang and Lundholm, 1993, 1996). Reg FD resulted in a decline in the quality and quantity of information disclosures, making it more difficult to forecast future earnings (Bailey et al., 2003). It also resulted in increased information uncertainty and complexity of the forecasting task, driving analysts to search privately for additional information. Analyst access to private information was further restricted following the Global Research Analyst Settlement in December 2002, which penalized analysts of top investment banks for issuing overly optimistic forecasts. De Franco et al. (2007) report evidence of a reduction in analyst misleading behavior after the settlement. Although these regulations helped protect investors, they left analysts in a difficult position by putting pressure on them not to bias their forecasts. Analysts abide by the regulations at the expense of jeopardizing their relationships with company managers and reducing their access to timely information. One way in which analysts can offset the effect of the loss of private information on the quality of their forecasts is by disclosing a BBA. But disclosing a BBA may also allow analysts to distract attention from bias in their forecasts.

Our analysis contributes to the literature on the content of analyst reports (Previts et al., 1994; Rogers and Grant, 1997; Asquith et al., 2005), although our study differs from previous research in that it is the first to establish a link between the content of analyst reports and the quality of the forecast output. Analysts have only recently started to include a valuation scenario section in their reports and to highlight a BBA.[3] We acknowledge that there may be an association between target price quality and other content of analysts' reports. However, as the BBA is more visible to investors and is directly related to the target price output, unlike other supplemental information, it is more relevant for target price accuracy. We therefore expect the findings of our study to improve our understanding of the determinants of analyst target price accuracy. The study should be of interest to academics wishing to understand the properties of analyst target prices and to investors wanting to assess the quality of analyst report outputs. It should also be of interest to investment banks trying to improve the quality of their research and to financial economists trying to find a way to distinguish ex ante which analysts are more accurate.

2. Prior research and hypothesis development

Evidence shows that target price revisions are associated with significant and immediate market reactions (Brav and Lehavy, 2003; Asquith et al., 2005; Da and Schaumburg, 2011). This quantifies the value of including target prices in analyst reports and suggests that knowing the determinants of target price quality is relevant to investors. These issues are

[3] On Investext, the number of reports including a BBA during 1999–2004 is less than 30 reports annually.

especially relevant when other research finds that investment portfolios formed on target prices generate returns that are substantially lower than ex ante returns implied by target prices (Brav and Lehavy, 2003; Barber et al., 2001) and that the market underreacts to target price revisions (Kreutzmann et al., 2010).

Target price accuracy has received considerable attention in the recent literature (Asquith et al., 2005; Bonini et al., 2010; Demirakos et al., 2010; Kerl, 2011; Bonini et al., 2011; Bradshaw et al., 2012). This research finds larger target price 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. Therefore, the literature does not offer conclusive evidence on whether analyst incentives reduce target price accuracy.

Evidence on analyst ability is also limited. Bradshaw et al. (2012) examine the accuracy of target prices and whether analysts have persistent differential forecasting ability. While they find evidence of such persistence, they 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 supporting evidence. De Vincentiis (2010), however, shows that the number of firms covered by the analyst 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 company 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.

In this paper, we examine the effect of a BBA on analyst target price accuracy. We first explore the determinants of whether an equity report includes a BBA. No prior research studies the underlying incentives and reasons for supplementing target prices with a BBA. We predict that the level of uncertainty about the company's future performance determines whether a report includes a BBA. When investment in a stock is associated with high uncertainty, the company's actual cash flows or earnings can diverge substantially from expectations making it difficult to project target prices. We conjecture that when analysts are uncertain about their valuation model inputs, they are more likely to support their target prices with a BBA. We test the following BBA information uncertainty hypothesis.

H1: *Equity analysts supplement valuations with a BBA when there is greater information uncertainty about firm value.*

Analyst incentives may also determine the choice to provide a BBA. On the one hand, analysts may have incentives to sacrifice accuracy in order to generate trading commissions and underwriting business for their bank and to maintain access to management. On the other hand, they have career concerns relating to their reputation and star ranking. Analysts facing greater conflicts of interests may provide a BBA in an attempt to signal that their forecasts are credible and hide their bias. This leads to the BBA analyst incentives hypothesis.

H2: *Equity analysts supplement valuations with a BBA when they face higher incentives to bias their forecasts.*

After examining the determinants of whether a report includes a BBA, we test the effect of this on analyst target price error. There are two possible outcomes to this analysis. A BBA can improve or reduce target price accuracy depending on analyst incentives.

A BBA can improve target price accuracy by helping analysts to account for information uncertainty in their valuations. Zhang (2006a) shows that analyst forecast error generally increases with greater information uncertainty, being positive in the case of good news and negative in the case of bad news. Because a BBA requires analysts to examine how changes in underlying fundamentals affect firm value, it may reduce their tendency to underestimate or overestimate the effect of information uncertainty on value and consequently reduce forecast error. Disclosing a BBA achieves this goal of reducing analyst error 'by forcing analysts to think more carefully and to critique their analysis more deeply with the goal of minimizing the impact of behavioral bias' (Srinivasan and Lane, 2011, p. 6). Moreover, the information that analysts convey to the market through their BBA may help investors improve their understanding of analyst valuations and their assessment of risk. Interpreting a target price supplemented with a BBA is more meaningful than interpreting a target price in isolation. Supplementing target price with a BBA provides investors with a richer set of information to assess whether the target price is associated with a larger upside potential or downside risk. A BBA is particularly useful to investors because by making risk explicit, it gives information about the 'unknown' and increases the credibility of analyst valuations, whereas a target price estimate on its own conveys a 'false sense of certainty and accuracy' and does not allow investors to understand analysts' assessments of the risk–reward trade-off associated with the investment (Srinivasan and Lane, 2011, p. 4). A BBA may, therefore, improve the investor response to information contained in analyst target prices and reduce the effect of information uncertainty on the market reaction.

On the other hand, a BBA might not be effective in reducing analyst forecast error if analysts provide a BBA in an attempt to signal credibility and disguise their biased forecasts. This leads to our second hypothesis, the main hypothesis of the paper. This hypothesis examines whether, controlling for the factors that determine whether a report includes a BBA, reporting a BBA increases target price accuracy.

H3: *Supplementing a valuation with a BBA improves target price accuracy.*

3. Sample and data

We use a cross-sectional sample of equity reports covering companies listed on U.S. stock markets. We download equity reports from Investext issued during January 2008 to December 2009. This is the first period when a reasonable number of observations is available for analysis and, because these data are hand-collected, we limit the sample period to two years.

The sample comprises two main groups: reports with bull and bear target prices (BBA reports) and reports with no such analysis (non-BBA reports). We use Investext's search facility to identify our samples. We search Investext equity reports using combinations of natural logic statements to identify (BBA) reports that contain words commonly used to refer to scenario analysis such as *bull case and bear case*, *high case and low case*, *upside case and downside case*, etc.[4] To identify common words that analysts use to refer to bull and bear target prices, we analyze around 950 (out-of-sample) reports. We then use negative natural logic combinations in the search query to generate (non-BBA) reports that do not include any

[4] An example of a logical statement used is: (bull case AND bear case) OR (high case AND low case) OR (upside case AND downside case).

of the above words. We read the generated analyst reports from both search queries in entirety to ensure that no analyst report tabulates a BBA without using the specific words in our search queries. This procedure validates our research method and provides further assurance that our classification of reports into BBA and non-BBA samples is accurate.

Several financial databases summarize earnings forecasts, recommendations, and target prices (e.g., Zacks Investment Research, First Call and I/B/E/S). There are currently no databases, however, providing similarly compiled information on bull and bear case target prices. The only way to collect this information is to read individual analyst reports and hand code their content. Therefore, we hand code reports for the following 12 data fields: report title, stock official ticker, report number (Investext Plus identifier), name of investment bank or research department, analyst name, report date, current target price, current market price, bull case target price, bear case target price, current EPS forecast, and current stock recommendation. We record recommendation levels rather than recommendation changes following Kreutzmann et al. (2010).

We exclude all reports that provide a scenario analysis but no target price. We also exclude a small number of reports that include a scenario analysis but only for EPS forecasts. We exclude reports that disclose a target price or earnings forecast in a foreign currency for cross-listed firms and with no target price or earnings estimate in US dollars. Applying these filters eliminates 152 reports. Finally, the only large research department not contributing to Investext is Goldman Sachs. Therefore, our sample does not include Goldman Sachs reports. While unavoidable, this may bias our sample. Our final sample comprises 7,692 equity reports, 1,710 companies, 47 (Fama and French, 1997) industries, 964 analysts, and 55 brokerage firms. Table 1 gives the industry distribution of the sample reports.[5] Table 2 lists the investment brokerage firms in the treated and control samples. Among the brokerage firms, Morgan Stanley contributes 75% of the BBA reports.[6]

[Tables 1 and 2 no earlier than here]

Other data sources are: I/B/E/S for the number of analysts following a company, the stock recommendation translation file, historical target prices, and consensus EPS estimates; CRSP for company age, stock prices, and returns; Compustat for cash flows, actual earnings, leverage data, and S&P credit rating changes; Thomson One Banker for investment bank affiliation; *Institutional Investor* for All-American Research Team Analysts data; and Thomson Reuters 13f files for institutional ownership data.

[5] Industry classifications are from Fama and French (1997).
[6] Subsequent sections discuss and analyze the role of Morgan Stanley reports.

We match Thomson One Banker underwriter names to Investext broker names using the I/B/E/S estimator translation file. We define affiliated investment banks as those serving as either lead or co-lead managers for a given equity or debt offering. All others are unaffiliated.[7] We include all types of equity offerings: initial public offerings (IPO), seasoned equity offerings (SEO), and convertible stock offerings in the affiliation sample. Prior research classifies an investment bank that offers underwriting services to a company at the most recent IPO, SEO, or debt offering at the beginning of the sample period as affiliated and remaining affiliated throughout the sample period as long as the company does not issue another offering in which the investment bank is not involved. In our sample, the affiliation variable takes the value one starting from the offering announcement date and ending at most one year after the offering. Ideally, the affiliation dummy should take the value one when the corporate finance department and the issuer sign the mandate letter. Since this information is not available, the affiliation designation indicates the affiliation relationship starting from the offering announcement. After completing the distribution of securities, the investment bank is no longer at risk from the issue and is likely to focus on new clients and offerings. Even if the relationship continues, it will not be as strong as at the time of the offering. We thus assume that, in the absence of further developments, the affiliation relationship between the investment bank and issuer ends after one year.

We collect data on analyst rankings from *Institutional Investor*. Every year, *Institutional Investor* surveys fund managers and other institutional investors to determine, by industry, the analysts who provided the top quality research during the year. Money managers nominate and evaluate analysts based on their accuracy, frequency of coverage, and the market reaction to their forecasts. *Institutional Investor* tabulates the results and announces the All-America Research Team in its October issue. It also tabulates the top ten investment banks for the year. We collect these data for 2007–2009 and match the data with the analyst reports. If analysts are in the All-America Team, we classify them as star analysts in all research report observations following the *Institutional Investor* October issue until the next October issue.[8] Because *Institutional Investor* does not follow an analyst or investment bank coding that matches Investext data, we match the *Institutional Investor* dataset, which comes in a text file, with our other data files using analyst last name, first initial, and research department.

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[7] We do not classify non-managing syndicate members as affiliated with the issuer because they are not involved in the pricing aspects of the offering.
[8] Our *Institutional Investor* All-America team ranking classification includes first, second, and third team analysts as well as runners up.

Our main variable of interest is target price accuracy. 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, *TPError*, as the absolute value of the target price minus the stock price at the end of the target price forecast horizon divided by the current market price.

4. Research design

We want to measure the impact of disclosing a BBA on target price accuracy. Analysts may choose to supplement a report on a particular company with a BBA, however, making it difficult to determine causation. Also, we observe target price accuracy resulting from the analyst decision, but not from decisions not made. We cannot, therefore, evaluate the effects of the analyst decision by comparing outcome differences for a given target price.

The decision to issue a report including a BBA is unlikely to be random. Information uncertainty and analyst incentives likely determine this choice. Moreover, the impact across companies, or the treatment effect, is unlikely to be homogenous. These differential effects also influence the analyst decision process and so are likely to correlate with the treatment effect. Consequently, an estimate of the treatment effect using ordinary least squares (OLS) is biased and suffers from an identification problem (Blundell and Costa Dias, 2000).

To eliminate selection bias, we consider the target price performance consequences of including a BBA using propensity score-matching (PSM) (Rosenbaum and Rubin, 1983) combined with a difference-in-differences (DD) analysis. PSM helps solve the problem of selection bias by balancing observed differences between groups. However, it relies on the assumption that observables determine selection. If there are unobserved analyst or company effects, results from PSM are biased. For example, while information uncertainty is measurable, analyst incentives are not completely measurable.[9] Therefore, we combine the PSM methodology with a DD analysis. A combined PSM–DD procedure lets us compare the target price accuracy of BBA and non-BBA reports while accounting for unobserved or unmeasured analyst and company effects, so the unobserved bias cancels out through differencing. This combined analysis should be more robust and has the potential to significantly improve the quality of the results (Blundell and Costa Dias, 2000).

[9] The component of analyst ability related to skill can become measurable over time. However, the component of analyst ability related to access to private information is difficult to quantify.

The propensity score is the conditional probability of receiving treatment. The treatment of interest is a BBA supporting target prices. The modelling problem is evaluating the causal effect of supporting analyst target prices with a BBA on *TPError*. The effect of including a BBA in report j is

$$TPError_j^1 - TPError_j^0 \qquad (1)$$

where $TPError_j^1$ is the target price error when the analyst report includes a BBA, and $TPError_j^0$ is the error of the (hypothetical) target price *had the analyst report not included a BBA*, The fundamental problem of causal inference is that we do not observe the counterfactual, $TPError_j^0$. To estimate this, we employ PSM to pair each BBA report with a set of non-BBA reports, based on observable variables. The propensity score model estimates the conditional probability of including a BBA given observable features of analysts and the company. Accordingly, we first estimate the probability that an analyst report includes a BBA (i.e., the propensity score) using the logistic regression,

$$P(BBA_{ijkt} = 1) = h(X_{ik}\beta) \qquad (2)$$

where BBA_{ijkt} is a dummy variable that indicates whether report j by analyst k for company i at time t includes a BBA, X is a vector of covariates determining the analyst decision, and P denotes the propensity score.

Using kernel matching, we match BBA to non-BBA reports based on the estimated propensity scores.[10] Kernel matching computes the distance of propensity scores of each BBA report from all non-BBA reports. Denoting a non-BBA report by j*, kernel matching calculates a weighting function, $w(j, j^*)$, for each report j by assigning a large value of $w(j, j^*)$ to a j* that is a short distance in terms of propensity score from j, and a small value of $w(j, j^*)$ to a j* that is a long distance in propensity score from j (Guo and Fraser, 2010, p. 259). The average treatment effect for the treated, ATT, is

$$ATT = \frac{1}{n}\sum_j \left[TPError_j^1 - \sum_{j^*} w(j, j^*) TPError_{j^*}^0 \right] \qquad (3)$$

where n is the number of matched BBA reports, $TPError_j^1$ is the error of BBA report j and $TPError_{j^*}^0$ is the error of non-BBA report j*. The term $\sum w(j, j^*) TPError_{j^*}^0$ distinguishes the

[10] We match using program *psmatch2* of Leuven and Sianesi (2003).

kernel-based matching approach as it measures the weighted average target price error of all non-BBA reports that match to report *j* on the propensity score.[11]

A major advantage of this matching method is that we can combine it with other methods to produce more accurate estimates and relax some strong conditions. Heckman et al. (1997, 1998) introduce a special version of the estimated average treatment effect on the treated using DD. They suggest combining PSM with DD to eliminate the selection bias that stems from unobserved characteristics. Combining PSM with DD allows for an unobserved determinant of BBA disclosure as long as this is a separable component of the error term. In panel data studies, the separable component is naturally time-specific, as both treated and control groups are measured pre- and post-treatment. Blundell and Costa Dias (2000) suggest extending PSM–DD to repeated cross-sections of data. In our analysis, the separable component of the error-term is analyst-specific. This means our matching analysis considers whether the fact that an analyst issuing a report is the type of analyst who discloses a BBA affects differences in target price accuracy.

The DD estimator for the repeated cross-sections is

$$DD = \frac{1}{n}\sum\left[TPError_A^1 - \sum w(j, j^*)TPError_{j^*\in C}^0 - \sum w(j, j^*)(TPError_{j^*\in B}^0 - TPError_{j^*\in D}^0) \right] \quad (4)$$

where our sample comprises four groups, namely

A: BBA reports (the treatment group);

B: contemporaneous non-BBA reports for companies in A (non-BBA reports for BBA companies);[12]

C: non-BBA reports by the analysts in A (control group for BBA analysts); and

D: contemporaneous non-BBA reports for the companies in C, by the analysts in B (control group for non-BBA analysts).

To measure the impact of disclosing a BBA on target price accuracy, we estimate the kernel-based PSM–DD estimator taking as inputs BBA-analyst and BBA-company dummies, the propensity scores estimated in the logistic model of equation (2) to match observations from group A with observations from groups B, C, and D, and the identified matched pairs. We perform the matching three times for each BBA report (Blundell and Costa Dias, 2000) to identify the matched pairs from the treatment and control groups and to compute the differences in accuracy between groups A and C and groups B and D. We then obtain the DD

[11] Nearest neighbour matching is sensitive to definition. Kernel matching is less sensitive and more efficient (Guo and Fraser, 2010).

[12] To get a reasonable number of observations, the control group observations are from reports issued within a (−15, 15) day window of the release date of the treatment group report.

estimate using equation (4).[13] The combined PSM–DD approach extends the conventional DD estimator by conditioning on the propensity score and estimating the differences semi-parametrically. The PSM–DD estimator is more robust than the conventional DD estimator because it does not assume linearity (Caliendo and Kopeinig, 2008).[14]

5. Results

5.1. Determinants of whether a report includes a BBA

To estimate the propensity score for each sample observation, we identify the variables determining whether an equity report includes a BBA. While no prior research studies why equity reports include a scenario analysis, some research suggests reasons and situations that call for this. We draw on this literature to specify the propensity-score model.

One factor that may affect whether an analyst discloses a BBA is information uncertainty. Uncertainty can arise from the complexity of the forecasting task or from the information available to analysts. When a stock is associated with high risk, the company's cash flows or earnings can diverge substantially from expectations making it difficult to project target prices. The literature suggests several proxies for uncertainty. Zhang (2006b) shows that information uncertainty stems from the volatility of the company's underlying fundamentals and poor information available to analysts. He uses six measures of information uncertainty: company size, company age, analyst coverage, analyst forecast dispersion, and return and cash flow volatility. Company size measures uncertainty because small companies have less information and disclosures available to the market. Analyst following proxies for company disclosure practices. More analysts follow companies with more informative disclosures and less uncertainty (Lang and Lundholm, 1996).

The second factor that may determine the analyst decision to provide a BBA is analyst incentives. Analysts face reputational concerns and have incentives to signal credibility to maintain their reputation and disguise their forecast bias. While we cannot observe analyst incentives, previous research suggests several proxies to control for these incentives. Analyst bias can be driven by incentives to generate trading and underwriting business for their banks (Cowen et al., 2006; Jackson, 2005) and to maintain access to management. It can also be

[13] To implement this approach in Stata, we use the *diff* module of Villa (2009).

[14] Applying DD to a cross-section assumes the same analyst-effect holds across the treatment and control groups. Combining PSM with DD relaxes this assumption and can achieve a better job of controlling for observable differences between the matched groups.

curbed by the presence of high institutional ownership (Ackert and Athanassakos, 2003) and reputational and career concerns (Fang and Yasuda, 2009; Hong and Kubik, 2003).

Building on this, we estimate the following logistic propensity-score model, which estimates the probability that analyst reports include a BBA conditional on observable features of analyst expertise and the level of uncertainty about the company's future performance. We also include variables that directly affect target price accuracy.

$$\begin{aligned}\Pr(BBA_i = 1) = \; & \beta_0 + \beta_1 Age_i + \beta_2 Liq_i + \beta_3 CVol_i + \beta_4 EVol_i + \beta_5 RVol_i + \beta_6 Cov_i + \beta_7 \ln Cap_i \\ & + \beta_8 TPDisp_i + \beta_9 Bold_i + \beta_{10} Star_i + \beta_{11} InstOwn_i + \beta_{12} Affltd_i + \beta_{13} Exp_i \\ & + \beta_{14} StrongBuy_i + \beta_{15} Hold_i + \beta_{16} Sell_i + \beta_{17} ROA_i + \beta_{18} NegROA_i + \beta_{19} M/B_i \\ & + \beta_{20} NegM/B_i + \beta_{21} Lev_i + \beta_{22} CrdtUp_i + \beta_{23} CrdtDown_i + \beta_{24} LrgRevFreq_i \\ & + \beta_{25} EPSDev_i + \beta_{26} TPDev_i + \beta_{27} Momentum_i + \beta_{28} Horizon_i + \beta_{29} Morgan_i + u_i \end{aligned} \tag{5}$$

Equation (5) includes two groups of variables. The first consists of eight information uncertainty proxies that are likely to affect the choice to supplement a valuation with a BBA: company age (*Age*), stock liquidity (*Liq*), cash flow volatility (*CVol*), earnings volatility (*EVol*), stock return volatility (*RVol*), the number of analysts following a company (*Cov*), company size (ln *Cap*), and target price dispersion (*TPDisp*).[15] Our first hypothesis predicts a positive association between information uncertainty and the likelihood that a report includes a BBA. We expect company age, stock liquidity, company size, and analyst coverage to have negative coefficients, and cash flow volatility, earnings volatility, stock return volatility, and target price dispersion to have positive coefficients.[16]

[Table 3 no earlier than here]

The second group consists of variables that are related to analyst incentives: forecast boldness (*Bold*), an institutional investor star analyst dummy (*Star*), institutional ownership (*InstOwn*), an analyst affiliation dummy (*Affltd*), and analyst company-specific experience (*Exp*). Target price boldness is the return implied by the target price at the report release date. Previous research finds a negative relation between target price boldness and accuracy (Demirakos et al., 2010); aggressive analysts are more likely to be biased since they have higher confidence in their private information. Analyst affiliation is likely to compromise analyst objectivity and bias outputs (O'Brien et al., 2005). We expect forecast boldness and

[15] Table 3 defines all the variables.

[16] It is important to note that many of the uncertainty proxies are likely to influence target price accuracy since accuracy likely improves with lower fundamental risk and lower information uncertainty. Hence, it is not straightforward to identify suitable exclusion restrictions if we analyze this problem using a treatment effect selection model.

analyst affiliation to reduce target price accuracy and therefore to have positive coefficients in equation (5) in support of the analyst incentives hypothesis. Previous research shows a positive relation between forecast accuracy and analyst reputation (Stickel, 1992) and firm specific-experience (Mikhail et al., 1997; Clement, 1999). Star and experienced analysts, unlike other analysts seeking recognition and ranking, may have lower reputational concerns. Consequently these factors may reduce analyst incentives to disclose a BBA. Analysts are also less likely to bias their forecasts for stocks highly visible to institutional investors. However, it is debatable whether analysts would disclose a BBA to cover their bias when valuing stocks with high institutional ownership.

We include several control variables: stock recommendation categories (*StrongBuy*, *Hold*, *Sell*) control for the sensitivity of target price accuracy to analyst recommendations, while return on assets (*ROA*, *NegROA*), market to book ratio (*M/B*, *NegM/B*), and leverage (*Lev*) control for a company's financial performance. We control for credit rating upgrades (*CrdtUp*) and downgrades (*CrdtDown*), building on evidence of the relation between target price revisions and credit rating changes (Bonini et al., 2009). We include a dummy for analyst revision frequency (*LrgRevFreq*) because analysts who make more frequent revisions are less likely to herd (Clement and Tse, 2005; Jegadeesh and Kim, 2010). We also expect analysts with higher EPS forecasts and target price deviations from consensus to be less likely to herd. We therefore control for analyst EPS deviation from consensus (*EPSDev*) and analyst target price deviation from consensus (*TPDev*). Other controls include stock price momentum (*Momentum*), target price forecast horizon (*Horizon*), and 47 industry dummies. We control for the forecast horizon because of its effect on accuracy (Sinha et al., 1997). This is an important control because not all target price forecasts in our sample have a 12-month forecast horizon. We include industry dummies to control for unmeasured industry-specific differences between treatment and control observations.

Last, we include a Morgan Stanley dummy variable (*Morgan*) to control for the substantial concentration of Morgan Stanley reports in the treatment sample. Srinivasan and Lane (2011) point out that Morgan Stanley introduced the BBA framework with the aim of helping underperforming analysts improve their quantification of uncertainty. The ultimate goal of the framework was to encourage analysts to provide more useful information to clients and consequently increase analysts' chances of receiving institutional investor votes. In our sample, we find that some Morgan Stanley reports include a BBA while others do not. This suggests that, in practice, during our sample period, analysts at Morgan Stanley retained some discretion over whether to issue a report with a BBA or not. Therefore, including a Morgan

Stanley dummy is unlikely to control fully for the decision to include a BBA. We address the potential hidden analyst effect (e.g., analyst confidence) on the decision to include a BBA when we estimate the combined PSM–DD model.

Table 4, panel A presents descriptive statistics for the full sample for these variables while panel B gives summary statistics for the treatment and control groups of BBA and non-BBA reports and 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.

[Table 4 no earlier than here]

5.2. Univariate analysis

We first compare the key characteristics of BBA and non-BBA *analysts*. If these characteristics differ, we need to control for them when examining differences in accuracy between the two groups. Table 5 summarizes mean and median values for the two groups. Unconditionally, BBA analysts are more likely to be star and affiliated analysts. They have significantly more experience than non-BBA analysts and they produce EPS and TP forecasts with higher deviations from the consensus. BBA analysts have above average revision frequency for the companies they cover. Therefore, BBA analysts are less likely to herd on the consensus. This deviation from consensus suggests that BBA analysts have more confidence in their private information and that they are more likely to be biased. The number of sell recommendations BBA analysts issue is higher. These results suggest that unconditionally, BBA analysts are not the worst performing analysts. However, BBA analysts are less likely to issue target prices below current prices, another indication that they are more likely to be biased. BBA analysts also have unconditionally larger forecast errors. The univariate analysis suggests significant differences in the characteristics of BBA and non-BBA analysts. Nonetheless, it is not possible to draw conclusions about the characteristics of BBA analysts based on the unconditional results. Nor can we infer from this analysis based on the characteristics of BBA analysts whether they are more likely to have more or less accurate target prices.

[Table 5 no earlier than here]

Table 6 reports the results of a univariate analysis examining differences in mean and median target price accuracy between BBA and non-BBA *reports*. Panel A gives mean and median target price errors. We also divide the sample into two sub-samples depending on whether or not the target price exceeds the current stock price. The number of reports is greater for the former than the latter, indicating that analysts issue target prices more often when news is positive. For the full sample and the two sub-samples, mean and median target price errors are lower for BBA reports than for non-BBA reports. The *t*- and *z*-tests in panels B and C show that the differences in means are significant between the BBA and non-BBA groups for the full sample and the two sub-samples. Differences in medians, however, are insignificant. In general, the results indicate that when analysts supplement their target prices with a BBA, they tend to be more conservative. This result is more pronounced when analysts communicate negative news to the market.

[Table 6 no earlier than here]

Table 7 reports the sample distribution by recommendation level. In the full sample, buy recommendations are the most common, followed by hold recommendations with strong buy and sell recommendations being less frequent. This is in line with the literature that analysts are reluctant to issue negative information on companies. These proportions vary across the BBA and non-BBA samples, but the proportions of (i) strong buy or buy and (ii) hold or sell, are similar across the two samples. Table 7, panel B compares accuracy by recommendation level and shows that the mean forecast error is lowest when analysts issue sell recommendations. Panel C tests for differences in accuracy between BBA and non-BBA reports by recommendation level and shows that BBA reports are more accurate for all but strong buy recommendations. This may indicate that analysts issue more conservative forecasts when they support their valuations with a BBA.

[Table 7 no earlier than here]

Analyzing the correlation matrix of the key variables (table 8) shows high correlations between information uncertainty variables such as ln *Cap, EVol*, and *CVol*. While including all three variables in a regression likely causes multicollinearity, this is not an issue for PSM because estimating the effects of individual covariates is not the main aim. We also note that while being a BBA analyst and a star analyst are positively associated, consistent with table 5, BBA reports and star analyst are negatively associated, consistent with table 4. This indicates that while star analysts are more likely than non-star analysts to issue a BBA report anywhere in the sample, non-star analysts issue a greater proportion of BBA reports. Obviously, this is an unconditional result that does not control for other factors.

[Table 8 no earlier than here]

5.3. Testing for selection and hidden biases

To justify our research design, we first test for the existence of selection bias. We add to the BBA determination equation (5), the target price accuracy equation,

$$TPError_i = b_0 + b_1 BBAanalyst_i + b_2 BBAcompany_i + b_3 BBA_i + \langle Controls \rangle + e_i \quad (6)$$

where *BBAanalyst* is a dummy that equals one if the analyst provides a BBA anywhere in the sample, *BBAcompany* is a dummy that equals one if the company receives a BBA anywhere in the sample, and *BBA* interacts the two dummies. The control variables include all information uncertainty proxies and variables affecting target price accuracy in equation (5). We estimate ρ, the correlation between the error terms of the BBA determination and target price accuracy equations, σ, the standard error of the target price accuracy equation, and $\lambda = \rho\sigma$. We test whether $\rho = 0$ (or equivalently whether $\lambda = 0$). If $\rho = 0$, there is no selection bias and we do not need to estimate the propensity score model. If $\rho \neq 0$, we need to control for selection bias. As $\chi^2 = 22654.13$ ($p = 0.000$), we reject the null hypothesis and conclude that ρ is non-zero. Second, we test for hidden bias. As discussed earlier, PSM is not robust to hidden bias (i.e., the matching analysis assumes that only observables determine selection). An unobservable variable (e.g., analyst confidence about their information) that affects whether a report includes a BBA can introduce hidden bias. We use Rosenbaum's bounds test to determine how strongly the unmeasured unobserved variable must affect treatment selection to weaken the results from a matching analysis alone.[17] If the matching analysis results are sensitive to hidden bias, this justifies combining PSM with DD. Using Wilcoxon's signed-rank test, the sensitivity analysis shows that the results of matching alone become sensitive to hidden bias at gamma = 1.01.[18] As this is a small value (Guo and Fraser, 2010, p. 318), we conclude that our analysis is sensitive to hidden bias, and therefore, the analysis requires the PSM–DD combined estimation to control for additional bias.

5.4 The propensity-score matching procedure

Table 9 reports the results of the first stage of the PSM–DD estimation, which involves estimating propensity scores using equation (5). The table shows the determinants of whether a BBA supplements target price valuations. In testing our first hypothesis, we estimate the model in equation (5) excluding the Morgan Stanley dummy. Table 9, column 1 reports the

[17] We implement this test in Stata using the user-developed programme *rbounds* of Gangl (2004).
[18] Gamma is a sensitivity parameter that measures the departure from random treatment assignment, where a value of one corresponds to a purely random assignment.

results. The evidence suggests that analysts are more likely to include a BBA for companies with higher cash flow volatility, stock return volatility, and target price dispersion, and for larger firms. Analysts are also more likely to support valuations with a BBA for younger firms, and stocks with lower liquidity, earnings volatility, and analyst coverage. Consistent with our first hypothesis, coefficient signs on the information uncertainty proxies accord with expectations except for $\ln Cap$, where analysts are more likely to provide a BBA for larger firms. Because of the high correlations between the information uncertainty variables, the coefficients on some of the variables in column 1 are insignificant. When we estimate the model including each of the highly correlated variables one at a time, however, we get significant coefficients with the correct signs in each regression.

[Table 9 no earlier than here]

For the analyst incentive and control variables, we are more likely to observe a BBA with analyst affiliation, higher analyst experience, negative return on assets, higher market to book ratio, higher leverage, a credit rating upgrade, above average revision frequency, higher EPS deviation from consensus, higher target price deviation from consensus, higher stock price momentum, and sell recommendations. On the other hand, analysts are less likely to provide a BBA with higher forecast boldness, when an analyst is a star, with higher levels of institutional ownership, with strong buy and hold recommendations, following credit rating downgrades, and for target prices with shorter forecast horizons. The result that star analysts are less likely, conditionally, to disclose a BBA is consistent with our prediction that analysts disclose a BBA in the presence of factors that call for improving their credibility and their relationship with institutional investors. Star analysts have less incentive to disclose a BBA than do analysts who have not achieved market recognition.

We estimate the full model of equation (5), including the Morgan Stanley dummy, to estimate the propensity score and report the results in table 9, column 2. Following estimation of this logistic regression, we create a logit score and define the logit as the propensity score. We use the propensity score to identify the matched pairs between Groups A and C and between Groups B and D for our DD estimation.

5.5 Covariate balance between treatment and control samples

When matching observations on the propensity score, we impose a common support that causes the program to drop treatment observations with a propensity score above a maximum or below a minimum propensity score of the untreated observations. This ensures the program matches observations with common support. Nonetheless, it is essential to check that the treatment and control groups are similar along observable dimensions except for the treatment dummy. To assess the covariate balance between the treatment and control groups, we calculate several measures of the balancing of variables across the treatment and control groups before and after matching. First, we conduct *t*-tests of the equality of means in the treated and untreated groups after matching. Table 10 reports means of the treatment and control groups with *t*-statistics and (two-tailed) *p*-values for the matching. The *p*-values indicate that the matching algorithm successfully balances most of the covariates; most *t*-tests are insignificant ($p > 0.1$). Second, we estimate the standardized bias after matching, together with the reduction in bias achieved (in percentage). The standardized bias is the difference in the sample means of the treated and control groups as a percentage of the square root of the average of the sample variances in the treated and control groups. As table 10 shows, after matching, the bias falls significantly for most covariates.

[Table 10 no earlier than here]

We also report overall measures of covariate balance before and after matching. The first is the pseudo-R^2 from estimating the propensity score on all the variables in the logistic model before matching and the pseudo-R^2 from the same logistic model on the matched samples. A low pseudo-R^2 means there are no systematic differences in the distributions of the covariates between the treatment and control groups. Table 10, panel B reports pseudo-R^2s and *p*-values of a likelihood-ratio test for the joint significance of the standardized differences between the treatment and control groups before and after matching. The likelihood ratio test checks whether these differences are jointly insignificant. The low pseudo-R^2 (0.006) after matching and the insignificant likelihood ratio test support the hypothesis that both groups have the same covariate distribution after matching. The results of the four tests imply that there is no systematic difference in the distribution of covariates between the groups after matching.

5.6 Estimating the average treatment effect using PSM combined with DD

Table 11 reports the key results of the combined, semi-parametric PSM–DD matching estimation of the effect of supplementing target prices with a BBA. We use the estimated propensity score to match observations in group A with observations in groups B, C, and D. We then create an identifier for the matched A–B and C–D pairs. This step makes our cross-section data sample similar to a panel in the sense that each observation in the treatment (control) group with a BBA analyst matches with at least one observation from the treatment (control) group with no BBA analyst, allowing us to compute the difference in target price error along the analyst dimension. Our final step uses these differences to find the average treatment effect estimated from combining DD with PSM by computing the difference along the treatment dimension. The *Base Line* columns in table 11 give the target price errors for the two non-BBA analyst control groups, group D (reports by non-BBA analysts for companies for which BBA analysts do not include a BBA) and group B (reports by non-BBA analysts for companies for which BBA analysts include a BBA). Column $\mathrm{B}-\mathrm{D}$ reports the difference in target price error between matched observations in groups B and D. Similarly, the *Follow Up* columns give the target price errors of the BBA analyst control and treatment groups, group C (reports by BBA analysts for companies for which BBA analysts do not include a BBA) and group A (reports by BBA analysts for companies for which BBA analysts include a BBA). Column A − C gives the difference in target price error between matched observations in groups A and C. Finally, the last column gives the DD estimate.

[Table 11 no earlier than here]

The difference in target price error between observations in the two BBA analyst groups, A and C, is significantly negative (−0.240, p = 0.000), indicating that the target price accuracy of BBA analysts is higher in reports on companies where they include a BBA. But this does not control for differences in the companies in these two groups. The difference in target price error between observations in the two non-BBA analyst groups, B and D, is also significantly negative (−0.124, p = 0.000), indicating that the target price accuracy of non-BBA analysts is also higher in reports on companies for which BBA analysts include a BBA. Nevertheless, the DD matching estimate is significantly negative (−0.116, p = 0.008), which confirms that, after controlling for unobserved analyst effects, supplementing valuations with a BBA achieves higher accuracy (lower forecast error). The DD matching estimate is also economically significant as, without the reduction of 11.6%, the target price error of BBA reports, of 48.9% would be 23.7% higher.

6. Sensitivity analysis

Our first sensitivity analysis involves estimating a regression-adjusted matching model. The semi-parametric PSM–DD analysis in table 11 does not estimate the relation between covariates and target price accuracy. It is useful, therefore, to combine matching with regression adjustment on covariates. Regression-adjusted matching can reduce the bias of the matching estimator by reducing any differences remaining between the matched treated and control observations after matching. This achieves a similar purpose to PSM–DD except it uses regression to estimate the treatment effect. After obtaining the matched sample using kernel-based matching, we construct a subsample consisting of all matched treated and control observations. We then estimate regression (6) to obtain the conventional DD estimator, controlling for observed covariates and unobserved (analyst-specific) heterogeneity. The parameter of interest on the variable *BBA*, b_3, measures the change in target price error due to supplementing target prices with a BBA. The results, in table 12, column 1 report the coefficient on *BBA* as −0.111, which is similar to our estimate in table 11.

[Table 12 no earlier than here]

Table 12, column 2 reports the results of a conventional DD estimation of the effect on target price error of supporting target prices with a BBA, using equation (6) on the full sample (with no prior matching). While subject to multicollinearity, this model gives an estimated treatment effect of −0.113 ($p < 0.000$), again similar to our estimate in table 11. These results imply that supporting target prices with a BBA reduces the forecast error. The coefficient on *BBAanalyst* is positive, indicating that BBA analysts are on average more inaccurate or biased than other analysts, consistent with the univariate analysis. The coefficient on the Morgan Stanley dummy is insignificant, indicating that controlling for this variable does not directly influence analyst target price accuracy.[19] According to the DD estimation, target price accuracy improves with higher stock liquidity and credit rating changes, and for star analysts. Accuracy deteriorates with higher earnings, stock return volatility, target price dispersion, and target price boldness. These results support previous findings in the literature.

Our second robustness test addresses the sensitivity of the estimated treatment effect to failure of the common support condition. Imposing the common support restriction results in 175 dropped BBA reports. This means that 93 percent of the treatment group have common support. Although the number of observations dropped is small, deleting observations that fall outside the common support region can bias results. We therefore estimate the results without imposing the common support restriction and find no significant differences in the treatment effect (untabulated). The fact that these results do not differ implies that our results are not sensitive to failure of the common support condition. This accords with expectations, as Reynolds and DesJardins (2009) note that when the proportion of dropped observations is small, the estimated treatment effect is likely to be similar to the true treatment effect.

Last, we estimate the treatment effect on target price accuracy of reporting a BBA using Heckman's two stage selection model. This controls for any selection bias resulting from the decision to include a BBA, but it does not estimate the DD effect. In this model, we make

[19] Our results also hold when we remove Morgan Stanley reports from the sample.

assumptions about the required exclusion restriction. We specify liquidity, earnings volatility, return volatility, target price dispersion, boldness, analyst star status, institutional ownership, analyst affiliation, analyst experience, recommendation levels, market to book ratio, credit rating upgrades, a large revision frequency dummy, momentum, target price forecast horizon and the BBA indicator as determining selection (i.e., including a BBA in the report). We specify company age, liquidity, cash flow volatility, earnings volatility, market capitalization, analyst star status, analyst affiliation, ROA, negative returns on assets, leverage, credit rating downgrades, EPS deviation from consensus, target price deviation from consensus and the Morgan Stanley dummy as the variables affecting target price accuracy. The results, not tabulated, show a significant negative coefficient on the BBA indicator (−0.033, p = 0.014). In this model, the sign and magnitude of the coefficient on *BBA* in the treatment equation measures the net impact of including a BBA on the target price error, net of observed selection bias. This means that, other things equal, supporting target prices with a BBA in equity reports reduces the target price forecasting error compared with reports that do not include a BBA. However, these results rely on strong assumptions about the specification of the selection equation.

7. Conclusion

Understanding the value and usefulness of analyst target prices has recently become of interest to academics, practitioners, and investors. The contribution of this study is to analyze a new factor that is relevant for explaining target price accuracy, the presence of a bull–bear valuation analysis (BBA). We examine whether analysts who supplement their target prices with a BBA issue more accurate target prices.

We conjecture that target price accuracy improves when analysts support their valuations with a BBA. In theory, a BBA can help analysts and investors assess a stock's risk. A BBA can be crucial in calibrating the uncertainty analysts have about the future performance of a company. It is possible, however, that aggressive analysts use a BBA to conceal their bias, mislead investors, and communicate to the market that they are more credible. The recent rise in prominence of target prices coupled with the somewhat vague impression of their purpose motivates our investigation of whether a BBA reduces or increases analyst forecast error. We employ propensity-score matching combined with difference-in-differences to match observations with similar levels of uncertainty about future company performance but that differ in whether or not they include a BBA.

We find that forecasting accuracy varies systematically depending on whether analysts report a BBA. Analysts achieve a statistically and economically significant improvement in their target price accuracy when they disclose a BBA and we conclude that including a BBA in equity reports adds information value. This finding has implications for investors who can have more confidence in target prices supported by a BBA.

This study opens avenues for further research on analyst valuations. Through a BBA, analysts try to incorporate downside risk and upside potential into their target price estimates. Future research can investigate and provide more detail on how they do this. For example, do they adjust the discount rate or risk premium to reflect uncertainty or do they change their cash flow estimates? Analysts have started to embrace the idea of supplementing their reports with bull and bear target prices only recently. If investment banks recognize the value of analyst reports that include them, they may want to emphasize and expand resources to develop more and better risk assessment valuation techniques.

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Table 1. Sample distribution by industry

	BBA		Non-BBA		
Industry	Frequency	Percent	Frequency	Percent	Total
Agriculture	24	0.99	1	0.02	25
Aircraft	46	1.9	51	0.97	97
Alcoholic Beverages	17	0.7	9	0.17	26
Apparel	17	0.7	98	1.87	115
Automobiles and Trucks	16	0.66	61	1.16	77
Banking	106	4.38	237	4.52	343
Business Services	138	5.7	600	11.43	738
Business Supplies	15	0.62	49	0.93	64
Candy and Soda	15	0.62	2	0.04	17
Chemicals	21	0.87	115	2.19	136
Coal	6	0.25	25	0.48	31
Computers	82	3.39	324	6.17	406
Construction	1	0.04	52	0.99	53
Consumer Goods	39	1.61	73	1.39	112
Construction Materials	1	0.04	55	1.05	56
Defence	6	0.25	11	0.21	17
Electrical Equipment	32	1.32	65	1.24	97
Electronic Equipment	184	7.6	559	10.65	743
Entertainment	30	1.24	111	2.12	141
Fabricated Products	5	0.21	0	0.00	5
Food Products	85	3.51	67	1.28	152
Healthcare	11	0.45	111	2.12	122
Insurance	101	4.17	112	2.13	213
Machinery	67	2.77	141	2.69	208
Measuring and Control Equip	39	1.61	126	2.40	165
Medical Equipment	56	2.31	164	3.13	220
Miscellaneous	30	1.24	67	1.28	97
Nonmetallic Mining	4	0.17	23	0.44	27
Personal Services	65	2.68	29	0.55	94
Pharmaceutical Products	164	6.77	219	4.17	383
Petroleum and Natural Gas	311	12.85	294	5.60	605
Precious Metals	0	0	13	0.25	13
Printing and Publishing	0	0	48	0.91	48
Real Estate	0	0	13	0.25	13
Recreational Products	0	0	36	0.69	36
Restaurants, Hotel, Motel	0	0	73	1.39	73
Retail	9	0.37	445	8.48	454
Rubber and Plastic Products	45	1.86	11	0.21	56
Shipbuilding, Railroad Eq	101	4.17	7	0.13	108
Steel Works	3	0.12	37	0.71	40
Telecommunications	26	1.07	118	2.25	144
Textiles	151	6.24	8	0.15	159
Tobacco Products	15	0.62	5	0.10	20
Trading	57	2.35	237	4.52	294
Transportation	60	2.48	160	3.05	220
Utilities	177	7.31	74	1.41	251
Wholesale	43	1.78	135	2.57	178
Total	2,421	100	5,248	100	7,692

Notes: The distribution of BBA and non-BBA sample reports by industry. Industry classifications follow Fama and French (1997).

Table 2. Research departments by sample group

Research department	BBA Reports	Non-BBA Reports	Total
ARDOUR CAPITAL	0	3	3
NATIXIS BLEICHROEDER	0	101	101
AVONDALE PARTNERS LLC	0	82	82
FERRIS, BAKER WATTS, INC.	0	12	12
BARRINGTON RESEARCH ASSOCIATES INC	0	40	40
BEAR STEARNS AND CO INC	1	33	34
BERNSTEIN RESEARCH	0	17	17
BOENNING AND SCATTERGOOD INC	1	26	27
BREAN MURRAY, CARRET AND CO	0	56	56
BUCKINGHAM RESEARCH GROUP, INC.	5	66	71
CANACCORD GENUITY	0	201	201
CANTOR FITZGERALD AND COMPANY	0	32	32
HSBC GLOBAL RESEARCH	3	2	5
CARIS & COMPANY	0	112	112
CL KING AND ASSOCIATES	1	5	6
C.K. COOPER & CO.	1	0	1
CRAIG HALLUM CAPITA	0	80	80
ROTH CAPITAL PARTNERS, LLC	2	112	114
DESJARDINS SECURITIES	0	1	1
OPPENHEIMER AND CO	7	122	129
CREDIT SUISSE - NORTH AMERICA	92	871	963
FOX-PITT, KELTON, INC.	9	8	17
THINKEQUITY LLC	21	206	227
J.J.B. HILLIARD, W.L. LYONS, INC.	0	36	36
JANNEY MONTGOMERY SCOTT LLC	0	18	18
JEFFERIES & COMPANY, INC.	14	341	355
JESUP & LAMONT SECURITIES	0	39	39
JPMORGAN	48	369	417
KAUFMAN BROTHERS	0	93	93
LADENBURG, THALMANN & CO. INC.	5	42	47
DEUTSCHE BANK SECURITIES INC.	109	842	951
RODMAN & RENSHAW, INC.	0	10	10
MACQUARIE RESEARCH	5	34	39
MAXIM GROUP LLC	0	38	38
KEYBANC CAPITAL MARKETS	1	32	33
SOLEIL-MEDIA METRICS	0	6	6
MORGAN JOSEPH AND CO	0	26	26
KEVIN DANN AND PARTNERS	0	10	10
MORGAN STANLEY	1,817	54	1,871
NEEDHAM & COMPANY	3	0	3
WEDBUSH SECURITIES INC	1	204	205
RBC CAPITAL MARKETS (US)	23	0	23
RBC CAPITAL MARKETS (Canada)	20	115	135
SUNTRUST ROBINSON HUMPHREY CAPITAL	201	180	381
OCIETE GENERALE	0	7	7
STANFORD FINANCIAL GROUP	12	81	93
STERNE, AGEE & LEACH, INC.	4	256	260
DOUGHERTY & CO., LLC	0	22	22
SUSQUEHANNA FINANCIAL GROUP LLLP	2	78	80
COLLINS STEWART LLC	13	55	68
DAVENPORT & COMPANY LLC	0	38	38
CIBC WORLD MARKETS INC. (CANADA)	0	5	5
W.R. HAMBRECHT & CO.	0	8	8
WALL STREET STRATEGIES	0	29	29
ZACKS INVESTMENT RESEARCH	0	15	15
Total	2,421	5,271	7,692

Notes: The distribution of BBA and non-BBA reports by research department.

Table 3. Variable definitions

Symbol	Variable name	Definition
Affltd	Affiliation dummy	Equals one when the analyst is affiliated with the company through an investment banking relationship, zero otherwise.
Age	Company age	Log of the number of years since the company's data is first available on CRSP.
BBA	Bull–bear analysis dummy	Equals one when the report includes a bull–bear analysis, zero otherwise. This is the interaction of *BBAanalyst* and *BBAcompany*.
BBAanalyst	BBA analyst dummy	Equals one when the report is by an analyst who discloses a BBA in the sample, zero otherwise.
BBAcompany	BBA company dummy	Equals one when the report covers a company that receives a BBA in the sample, zero otherwise.
Bold	Target price boldness	Difference between the target price forecast and the current stock price divided by the current stock price.
Buy	Buy dummy	Equals one when the analyst stock recommendation is Buy, zero otherwise.
Cov	Analyst coverage	Log of the I/B/E/S number of analysts following the company in the previous year.
CrdtUp	Credit rating upgrade	Equals one if Standard and Poor's changes the credit rating of the company upward, zero otherwise.
CrdtDown	Credit rating downgrade	Equals one if Standard and Poor's changes the credit rating of the company downward, zero otherwise.
CVol	Cash flow volatility	Log of the standard deviation of the company's cash flow from operations (Compustat data item 308) over the previous five years.
EPSdev	EPS forecast deviation from consensus	Absolute value of the difference between the current analyst EPS forecast and the mean consensus forecast.
EVol	Company earnings volatility	Log of the standard deviation of the company's actual earnings (Compustat data item 18) over the previous year.
Exp	Company coverage experience	Number of years since the analyst first started providing coverage for the company.
Hold	Hold dummy	Equals one when the analyst stock recommendation is Hold, zero otherwise.
Horizon	Target price forecast horizon	Target price forecast horizon, in months.
InstOwn	Level of institutional ownership	Total number of shares held by institutional investors divided by the total number of shares outstanding.
Lev	Leverage ratio	The company's debt-to-assets ratio (in percent) for the year before the publication of the analyst report.
Liq	Stock liquidity	Highest ask price minus lowest bid price (over the preceding month) divided by the bid–ask midpoint over the month.
ln *Cap*	Market capitalisation	Log of market capitalization of the stock.

(*Continued*)

Table 3—*Continued*

Symbol	Variable name	Definition
LrgRevFreq	Large revision frequency dummy	Equals one if the number of target price revisions issued by a given analyst for a given stock in a given year is greater than the average number of revisions for that stock in that year, zero otherwise.
M/B	Market-to-book ratio	The company's market-to-book value ratio (if market-to-book ratio is positive).
Liq	Stock liquidity	Highest ask price minus lowest bid price (over the preceding month) divided by the bid–ask midpoint over the month.
Momentum	Price momentum	Log of the current price of the stock divided by the price of the stock 180 days before the release of the analyst report.
Morgan	Morgan Stanley indicator	Equals one for all Morgan Stanley reports, zero otherwise.
NegM/B	Negative market-to-book ratio	Equals one if the company's market-to-book ratio is negative, zero otherwise.
NegROA	Negative return on assets ratio	Equals one if the company's return on asset is negative, zero otherwise.
NegTP	Negative target price	Equals one if the analyst target price forecast is lower than the current market price, zero otherwise.
TPDev	Target price deviation from consensus	Absolute value of the difference between the analyst target price forecast and the mean consensus target price forecast.
TPDisp	Target price forecast dispersion	Standard deviation of all analyst target price forecasts during the previous quarter divided by current market price.
TPError	Target price absolute error	Absolute value of the target price minus the stock price at the end of the target price forecast horizon divided by the current market price.
ROA	Return on assets	The company's return on assets (in percent) for the year before the publication of the analyst report (if return on assets is positive).
RVol	Return volatility	Standard deviation of weekly excess returns on the stock over the preceding month.
Sell	Sell 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.
StrongBuy	Strong buy dummy	Equals one if the analyst stock recommendation is Strong Buy, zero otherwise.

Table 4. Descriptive statistics

Panel A: Descriptive statistics, full sample (*N* = 7,692)					
Variable	Mean	Median	Std. Dev.	Min	Max
BBA	0.315	0.000	0.464	0.000	1.000
BBAanalyst	0.670	1.000	0.470	0.000	1.000
BBAcompany	0.378	0.000	0.485	0.000	1.000
Age	2.651	2.743	0.964	−2.403	4.145
Liq	0.224	0.169	0.172	0.024	1.669
CVol	4.763	4.622	1.689	0.000	11.269
EVol	4.654	4.586	1.678	−0.035	10.707
*RVol**	0.066	0.057	0.036	0.022	0.240
Cov	2.337	2.398	0.606	0.000	3.555
ln *Cap*	21.715	21.617	1.748	16.360	26.944
*TPDisp**	0.254	0.175	0.277	0.024	1.943
*Bold**	0.254	0.185	0.377	.−0.427	2.304
Star	0.085	0.000	0.279	0.000	1.000
InstOwn	0.784	0.807	0.223	0.000	1.843
Affltd	0.122	0.000	0.328	0.000	1.000
Exp	4.144	3.000	3.456	0.000	10.000
StrongBuy	0.087	0.000	0.282	0.000	1.000
Hold	0.387	0.000	0.487	0.000	1.000
Sell	0.084	0.000	0.277	0.000	1.000
*ROA**	6.816	5.687	6.151	0.000	28.616
NegROA	0.153	0.000	0.360	0.000	1.000
*M/B**	3.917	2.677	4.582	0.000	30.606
NegM/B	0.020	0.000	0.139	0.000	1.000
*Lev**	21.019	19.748	17.241	0.000	50.722
CrdtUp	0.047	0.000	0.213	0.000	1.000
CrdtDown	0.046	0.000	0.210	0.000	1.000
LrgRevFreq	0.431	0.000	0.495	0.000	1.000
*EPSDev**	0.341	0.130	0.612	0.000	4.060
*TPDev**	6.295	3.500	8.726	0.000	54.626
*TPError**	0.534	0.429	0.465	0.007	2.830
Momentum	−0.218	−0.177	0.489	−2.926	3.098
Horizon	11.837	12.000	1.104	1.000	24.000

(*Continued*)

Table 4—*Continued*

Panel B: Descriptive statistics: BBA and non-BBA reports								
	Mean		Median		Mean difference		Median difference	
Variable	BBA	non-BBA	BBA	non-BBA	*t*-stat	*p*-value	*z*-stat	*p*-value
Age	2.744	2.608	2.876	2.697	−5.739	0.000	−7.732	0.000
Liq	0.189	0.240	0.145	0.182	12.331	0.000	15.102	0.000
CVol	5.566	4.395	5.430	4.248	−29.826	0.000	−28.723	0.000
EVol	5.387	4.318	5.359	4.167	−27.158	0.000	−25.824	0.000
*RVol**	0.060	0.069	0.051	0.059	10.213	0.000	14.118	0.000
Cov	2.515	2.255	2.565	2.303	−17.832	0.000	−17.976	0.000
ln *Cap*	22.616	21.301	22.561	21.176	−32.702	0.000	−31.098	0.000
*TPDisp**	0.222	0.270	0.157	0.186	7.043	0.000	9.351	0.000
*Bold**	0.252	0.254	0.196	0.179	0.274	0.784	−2.071	0.038
Star	0.076	0.089	0.000	0.000	1.958	0.050	1.958	0.050
InstOwn	0.763	0.793	0.784	0.820	5.553	0.000	7.632	0.000
Affltd	0.219	0.078	0.000	0.000	−17.832	0.000	−17.475	0.000
Exp	5.595	3.478	7.000	2.000	−26.018	0.000	−24.275	0.000
StrongBuy	0.017	0.119	0.000	0.000	14.967	0.000	14.755	0.000
Hold	0.335	0.411	0.000	0.000	6.371	0.000	6.354	0.000
Sell	0.125	0.065	0.000	0.000	−8.936	0.000	−8.891	0.000
*ROA**	7.135	6.670	5.962	5.550	−3.083	0.002	−3.131	0.002
NegROA	0.128	0.164	0.000	0.000	4.058	0.000	4.054	0.000
*M/B**	4.292	3.744	2.828	2.599	−4.878	0.000	−3.038	0.002
NegM/B	0.022	0.019	0.000	0.000	−0.969	0.333	−0.969	0.333
*Lev**	23.791	19.745	22.824	17.285	−9.614	0.000	−10.689	0.000
CrdtUp	0.058	0.042	0.000	0.000	−3.018	0.003	−3.016	0.003
CrdtDown	0.045	0.047	0.000	0.000	0.473	0.636	0.473	0.636
LrgRevFreq	0.483	0.407	0.000	0.000	−6.277	0.000	−6.262	0.000
*EPSDev**	0.441	0.296	0.170	0.120	−9.709	0.000	−8.617	0.000
*TPDev**	7.812	5.598	3.929	3.300	−10.405	0.000	−6.498	0.000
*TPError**	0.496	0.552	0.419	0.436	4.878	0.000	1.477	0.140
Momentum	−0.146	−0.251	−0.092	−0.221	−8.814	0.000	−9.795	0.000
Horizon	11.511	11.987	12.000	12.000	17.941	0.000	20.121	0.000

Notes: Descriptive statistics for the sample variables. Panel A gives the mean, median, standard deviation, and minimum and maximum values of the variables for the full sample. Panel B reports descriptive statistics for the sample variables for reports including a bull–bear analysis (BBA sample) and reports with no bull–bear analysis (non-BBA sample). The sample includes 5,271 non-BBA reports and 2,421 BBA reports. Variables marked with * are winsorized at the upper and lower 1% levels to reduce outlier effects.

Table 5. Characteristics of BBA analysts

	Mean		Mean difference		Median		Median difference	
	BBA analysts	non-BBA analysts	*t*-value	*p*-value	BBA analysts	non-BBA analysts	*z*-value	*p*-value
Star	0.107	0.039	−10.1	0.000	0.000	0.000	−10.0	0.000
Affltd	0.164	0.037	−16.3	0.000	0.000	0.000	−16.0	0.000
Exp	4.869	2.672	−27.5	0.000	5.000	2.000	−26.6	0.000
EPSdev	0.379	0.265	−7.7	0.000	0.150	0.110	−7.4	0.000
TPdev	6.662	5.548	−5.3	0.000	3.600	3.227	−4.5	0.000
LrgRevFrq	0.456	0.380	−6.3	0.000	0.000	0.000	−6.3	0.000
Sell	0.095	0.061	−5.0	0.000	0.000	0.000	−5.0	0.000
NegTP	0.159	0.177	2.0	0.042	0.000	0.000	3.2	0.002
TPError								
Full sample	0.543	0.516	−2.4	0.016	0.446	0.398	−3.7	0.000
TP > current price	0.568	0.531	−2.9	0.004	0.473	0.416	−4.4	0.000
TP ≤ current price	0.413	0.447	1.4	0.160	0.322	0.339	1.3	0.196

Notes: Comparison of the characteristics of BBA and non-BBA analysts. BBA analysts are analysts who issue a bull–bear analysis anywhere in the sample. Non-BBA analysts are analysts who do not issue a bull–bear analysis in the sample. The table gives the mean and medians of variables related to analyst characteristics and the results of mean and median differences tests. The means and medians are based on a sample of 5,155 BBA analyst reports and 2,537 non-BBA analyst reports. Table 3 provides variable definitions.

Table 6. Target price accuracy: univariate analysis

Panel A: Mean and median TPError

	N		Mean		Median	
Group	BBA	Non-BBA	BBA	Non-BBA	BBA	Non-BBA
Full Sample	2,421	5,271	0.496	0.552	0.419	0.436
TP > Current price	2,068	4,347	0.517	0.574	0.447	0.460
TP ≤ Current price	353	924	0.371	0.445	0.315	0.335

Panel B: TPError mean difference, two-tailed *t*-test

	Full-sample		*TP > current price*		*TP ≤ current price*	
	t-value	*p*-value	*t*-value	*p*-value	*t*-value	*p*-value
BBA and non-BBA	4.878	0.000	4.526	0.000	2.875	0.005

Panel C : TPError median difference, two-tailed *t*-test

	Full-sample		*TP > current price*		*TP ≤ current price*	
	z-value	*p*-value	*z*-value	*p*-value	*z*-value	*p*-value
BBA and non-BBA	1.477	0.140	1.411	0.158	1.546	0.122

Notes: Results of *t*-tests for differences in mean and median accuracy between BBA and non-BBA reports. BBA represents the sample of reports with a bull–bear analysis. Non-BBA represents the sample of reports with no bull–bear analysis. Panel A gives the sample distribution across the two groups and the mean and median accuracy for each group. Panel B gives the results of mean difference tests and panel C the results of median difference tests. *TPError* is 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 7. Sample distribution and accuracy by recommendation level

Panel A: Distribution of reports

	BBA		Non-BBA		Total	
		%		%		%
Strong Buy	41	1.7	627	11.9	668	8.7
Buy	1,267	52.3	2,139	40.6	3,406	44.3
Hold	810	33.5	2,164	41.1	2,974	38.7
Sell	303	12.5	341	6.5	644	8.4
Total	2,421		5,271		7,692	

Panel B: Mean TPError (%)

	BBA	Non-BBA	Full sample
Strong Buy	46.66	55.10	54.59
Buy	56.15	61.30	59.39
Hold	42.87	52.98	48.14
Sell	40.57	48.71	44.88

Panel C: TPError mean difference between non-BBA and BBA

	t-stat	*p*-value
Strong Buy	1.105	0.269
Buy	3.102	0.002
Hold	3.849	0.000
Sell	2.444	0.015

Notes: BBA represents the sample of reports with a bull–bear analysis. Non-BBA represents the sample of reports with no bull–bear analysis. Panel A gives the distribution of reports by recommendation level. Panel B reports accuracy in mean percentage for the two groups and the overall sample across the four recommendation levels. Panel C reports results for mean differences. *TPError* is 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 8. Pearson correlation matrix

	TPError	*BBA*	*BBAanalyst*	*BBAcompany*
BBA	−0.0555*			
BBAanalyst	0.0274	0.4754*		
BBAcompany	−0.0656*	0.8697*	0.2700*	
Age	−0.1320*	0.0653*	0.0292*	0.0881*
Liq	0.1519*	−0.1393*	−0.0332*	−0.1493*
CVol	−0.1074*	0.3220*	0.1779*	0.3834*
EVol	−0.0380*	0.2958*	0.1606*	0.3573*
RVol	0.3654*	−0.1157*	−0.0227*	−0.1431*
Cov	−0.1024*	0.1993*	0.0813*	0.2747*
ln *Cap*	−0.2505*	0.3494*	0.1508*	0.4185*
TPDisp	0.4179*	−0.0801*	−0.0164	−0.0905*
Bold	0.5127*	−0.0348*	0.0157	−0.0445*
Star	−0.0410*	−0.0223*	0.1142*	−0.0350*
InstOwn	−0.0681*	−0.0632*	0.0124	−0.0753*
Affltd	−0.0203	0.1993*	0.1824*	0.1653*
Exp	−0.0938*	0.2844*	0.2990*	0.2265*
StrongBuy	0.0078	−0.1682*	−0.2628*	−0.1222*
Hold	−0.0898*	−0.0725*	0.0476*	−0.0796*
Sell	−0.0554*	0.1014*	0.0573*	0.0859*
ROA	−0.1414*	0.0351*	−0.0185	0.0652*
NegROA	0.1807*	−0.0462*	−0.0636*	−0.0660*
M/B	0.0106	0.0555*	0.0213*	0.0742*
NegM/B	0.0122	0.0110	−0.0064	0.0250*
Lev	0.0595*	0.0910*	0.0888*	0.1013*
CrdtUp	−0.0403*	0.0344*	0.0213*	0.0380*
CrdtDown	−0.0526*	−0.0054	−0.0166	−0.0083
LrgRevFreq	0.0310*	0.0714*	0.0719*	0.0619*
EPSDev	0.1653*	0.1100*	0.0878*	0.1035*
TPDev	0.0430*	0.1178*	0.0600*	0.1442*
Momentum	−0.2895*	0.1000*	−0.0646*	0.0978*
Horizon	−0.0029	−0.2004*	−0.0901*	−0.1728*

(*Continued*)

Table 8—*Continued*

	Age	*Liq*	*CVol*	*EVol*	*RVol*	*Cov*	ln *Cap*
Liq	−0.1224*						
CVol	0.3726*	−0.1248*					
EVol	0.3492*	−0.0851*	0.8842*				
RVol	−0.1977*	0.5341*	−0.1792*	−0.0985*			
Cov	0.2284*	−0.1049*	0.5428*	0.5261*	−0.1715*		
ln *Cap*	0.3735*	−0.2990*	0.8327*	0.7471*	−0.3903*	0.5836*	
TPDisp	−0.0914*	0.3442*	−0.0733*	0.0206*	0.3780*	−0.0518*	−0.3268*

Notes: Correlation matrix of key variables in the paper. Table 3 provides variable definitions. * indicates significance at 1%.

Table 9. Propensity-score estimation using logistic regression

	1		2	
	Coefficient	*p*-value	Coefficient	*p*-value
Age	−0.284***	0.000	−0.124	0.189
Liq	−0.986***	0.001	−0.15	0.692
CVol	0.05	0.576	0.018	0.881
EVol	−0.058	0.465	0.059	0.584
RVol	2.19	0.282	−0.815	0.693
Cov	0.065	0.645	0.082	0.663
ln *Cap*	0.392***	0.000	0.16	0.118
TPDisp	−0.447*	0.075	0.329	0.230
Bold	0.750***	0.000	0.178	0.383
Star	−0.891***	0.000	−1.666***	0.000
InstOwn	0.09	0.735	−0.622	0.114
Affltd	0.608***	0.000	−0.347*	0.097
Exp	0.128***	0.000	−0.034	0.198
StrongBuy	−1.826***	0.000	−0.837***	0.000
Hold	−0.081	0.485	0.038	0.810
Sell	1.247***	0.000	−0.041	0.881
ROA	0.004	0.752	−0.012	0.433
NegROA	0.246	0.199	0.14	0.614
M/B	0.013	0.325	−0.039**	0.012
NegM/B	0.333	0.387	0.669	0.241
Lev	0.007	0.122	0.005	0.359
CrdtUp	0.162	0.504	0.371	0.182
CrdtDown	−0.249	0.242	−0.215	0.524
LrgRevFreq	0.059	0.567	0.259*	0.067
EPSDev	0.319***	0.000	0.170*	0.085
TPDev	0.003	0.650	0.021***	0.006
Momentum	0.304***	0.006	0.282*	0.064
Horizon	−0.544***	0.000	−0.325***	0.000
Morgan			6.664***	0.000
Constant	−3.149*	0.090	−2.315	0.293
Industry Dummies	Yes		Yes	
Analyst report obs.	7,692		7,692	
Pseudo R^2	28.9%		68.29%	
Wald χ^2	721.62	0.000	1240.34	0.000

Notes: Logistic regressions of *BBA* on the variables determining analyst choice to supplement target prices with a BBA. The regressions include all proxies for information uncertainty, variables affecting target price accuracy, and control variables. The output of this regression, the probability of including a BBA in a report, is used to calculate the propensity score. Table 3 provides variable definitions.

Table 10. Covariate balance between matched pairs

Panel A: Covariate balance between matched pairs						
	Mean		*t*-test			
Variable	Treated	Control	*t*	*p* > *t*	Bias %	Bias reduction %
Age	2.733	2.719	0.49	0.623	1.5	89.40
Liq	0.188	0.190	−0.50	0.619	−1.3	95.90
CVol	5.524	5.598	−1.51	0.130	−4.6	93.70
EVol	5.339	5.407	−1.45	0.146	−4.3	93.60
RVol	0.060	0.060	0.37	0.708	1.1	95.80
Cov	2.510	2.523	−0.83	0.404	−2.4	94.70
ln *Cap*	22.573	22.622	−0.98	0.326	−3.0	96.30
TPDisp	0.218	0.222	−0.60	0.551	−1.5	91.40
Bold	0.250	0.243	0.32	0.750	0.7	92.30
Star	0.080	0.100	−2.33	0.020	−7.2	−47.20
InstOwn	0.766	0.769	−0.60	0.547	−1.7	87.70
Affltd	0.207	0.206	0.12	0.906	0.4	99.00
Exp	5.529	5.367	1.55	0.122	4.8	92.40
StrongBuy	0.018	0.021	−0.68	0.497	−1.1	97.30
Hold	0.337	0.329	0.54	0.591	1.6	90.10
Sell	0.126	0.135	−0.92	0.358	−3.1	84.80
ROA	7.156	7.091	0.35	0.724	1.1	86.00
NegROA	0.134	0.146	−1.19	0.233	−3.5	65.80
M/B	4.205	4.004	1.41	0.160	4.2	63.30
NegM/B	0.021	0.023	−0.46	0.642	−1.4	38.70
Lev	25.261	24.497	1.19	0.233	3.5	82.10
CrdtUp	0.060	0.085	−3.30	0.001	−11.6	−61.10
CrdtDown	0.047	0.047	−0.14	0.890	−0.4	64.40
LrgRevFreq	0.479	0.494	−0.97	0.331	−2.9	81.10
EPSDev	0.417	0.416	0.06	0.950	0.2	99.10
TPDev	7.433	7.745	−1.04	0.297	−3.3	85.90
Momentum	−0.141	−0.117	−1.85	0.065	−5.2	77.10
Horizon	11.896	11.907	−0.57	0.568	−0.8	97.60
Morgan	0.669	0.676	−0.50	0.618	−2.5	98.90
Panel B: Overall covariance balance test						
Pseudo R^2 before matching			0.213			
Pseudo R^2 after matching			0.006			
				p-value		
LR χ^2 before matching			2041.63	0.000		
LR χ^2 after matching			37.27	0.113		

Notes: Results of three balancing property tests for matching using propensity scores estimated excluding industry dummies. Panel A presents the balance test results for the matched pairs on all the covariates. Panel B presents the overall covariate balance tests results. Table 3 defines the variables.

Table 11. Kernel propensity score matching: difference-in-differences estimation

	Base Line			*Follow Up*			
Outcome Variable	Control D	Control B	B − D	Control C	Treatment A	A – C	DD (A − C) − (B − D)
TPERROR	0.613	0.490	−0.124	0.729	0.489	−0.240	−0.116
Std. Error	0.027	0.020	0.034	0.027	0.009	0.028	0.044
t-stat	22.81	−5.52	−3.68	4.92	−11.80	−4.21	−2.64
p-value	0.000	0.000	0.000***	0.000	0.000	0.000***	0.008***
Obs.	3277						

Notes: The (semi-parametric) matching difference-in-differences estimate of the effect of supplementing target prices with a BBA. The matching uses propensity scores estimated using all logit model variables of equation (5). Group A is the treatment group, the group of BBA reports. Groups B, C, and D are the control groups. Group B comprises reports by non-BBA analysts for companies for which BBA analysts include a BBA. Group C comprises reports by BBA analysts for companies for which BBA analysts do not include a BBA. Group D comprises reports by non-BBA analysts for companies for which BBA analysts do not include a BBA. Columns B − D and A − C report the difference in target price error between matched observations in the groups. Column DD reports the difference-in-differences estimate. Groups are matched with replacement. Means and standard errors are estimated by linear regression.
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table 12. Regression adjusted matching and conventional DD estimation of the effect of supporting valuations with a BBA on target price accuracy

	1		2	
TPError	Coef.	*p*-value	Coef.	*p*-value
BBAanalyst	0.063***	0.000	0.063***	0.000
BBAcompany	0.038	0.105	0.038	0.104
BBA	−0.111***	0.000	−0.113***	0.000
Age	−0.006	0.455	−0.005	0.531
Liq	−0.376***	0.000	−0.376***	0.000
CVol	−0.012	0.204	−0.011	0.247
EVol	0.027***	0.002	0.028***	0.002
RVol	3.518***	0.000	3.410***	0.000
Cov	−0.012	0.410	−0.010	0.474
ln *Cap*	−0.018*	0.069	−0.021**	0.034
TPDisp	0.211***	0.000	0.207***	0.000
Bold	0.508***	0.000	0.514***	0.000
Star	−0.034**	0.050	−0.034**	0.049
InstOwn	−0.002	0.949	0.004	0.875
Affltd	−0.018	0.276	−0.016	0.313
Exp	−0.002	0.337	−0.002	0.356
StrongBuy	−0.042**	0.019	−0.044**	0.014
Hold	0.003	0.786	0.002	0.900)
Sell	0.076***	0.003	0.078***	0.002
ROA	−0.003**	0.049	−0.003**	0.046
NegROA	−0.024	0.255	−0.025	0.251
M/B	0.004**	0.026	0.004**	0.016
NegM/B	−0.042	0.286	−0.032	0.401
Lev	0.000	0.586	0.000	0.552
CrdtUp	−0.070***	0.002	−0.073***	0.002
CrdtDown	−0.086***	0.004	−0.089***	0.002
LrgRevFreq	0.010	0.291	0.01	0.316
EPSDev	0.053***	0.000	0.048***	0.000
TPDev	0.001	0.447	0.000	0.748
Momentum	0.004	0.843	0.006	0.764
Horizon	−0.005	0.346	0.002	0.472
Morgan	0.016	0.439	0.021	0.314
Constant	0.502**	0.036	0.831***	0.000
Industry dummies	Yes		Yes	
Obs.	7517		7692	
Adjusted *R*-squared	39.6%		38.9%	

Notes: Results of (parametric) OLS regressions to estimate the difference-in-differences estimate of the effect of supplementing target prices with a BBA. The first column presents the results from regressing the accuracy measure *TPError* on the independent variable *BBA* and additional independent variables based on the matched sample. The matched sample matches observations from the treatment and control groups using propensity score matching. The second column presents the conventional DID estimation for the full sample. Standard errors are adjusted for clustering by analysts and companies to adjust for within cluster correlation. Table 3 provide variable definitions.