# The Earnings Forecast Accuracy, Valuation Model Use, and Price Target Performance of Sell-Side Equity Analysts

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## Abstract

This paper investigates whether sell-side analysts who produce accurate earnings forecasts also produce superior price target estimates. We extend Loh and Mian (2005) and document a positive association between earnings forecast accuracy and price target accuracy. Second, there is a positive association between earnings forecast accuracy and the profitability of trading strategies built from analysts' price targets. These results compliment Bradshaw and Brown (2005) who find no evidence of sustained ability to accurately forecast price targets. Our results suggest that the accuracy of price targets is associated with the accuracy of EPS forecast inputs. Results from preliminary tests of the association between price targets and *pseudo*-price targets derived from valuation models are consistent with those of Bradshaw (2002, 2004) and provide little evidence to suggest that the price target superiority of analysts in the highest EPS forecast accuracy quintile can be traced to the use of a more rigorous valuation approach.

*JEL Classification:*

*Key Words:*

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# 1. Introduction

Sell-side equity analysts collect, evaluate, and disseminate information about the future performance of the firms they cover. Most analysts' reports highlight three key summary measures: near-term forecasts of earnings; a price target reflecting the analyst's opinion about what the stock is currently worth; and a buy/sell stock recommendation. Textbook descriptions of fundamental equity analysis (e.g., Copeland, Koller, Murrin 2000; Penman 2004) stress a strict sequential—but perhaps idealized—relation among these three report components. Earnings forecasts, along with other data, are first used by the analyst as inputs to a formal multiperiod valuation model to produce a share price estimate known as the "price target."[1] The buy/sell recommendation is then determined by comparing the current market price of the stock against the price target. Adopting the standard nomenclature of analysts' stock recommendations, a Buy or Strong Buy recommendation indicates a stock that the analyst believes is underpriced (i.e., the price target exceeds the current market price), a Hold recommendation indicates a fairly priced stock, and a Sell recommendation indicates an overpriced stock.

This paper investigates whether sell-side analysts who produce more accurate earnings forecasts also produce superior price targets. Success in the forecasting task is assessed using traditional measures of analysts' forecast accuracy. Success in assigning price targets—the equity valuation task—is assessed by examining the behavior of future stock prices and realized returns. There are several reasons why earnings forecast accuracy may be unrelated to the quality of analysts' price targets. Bradshaw (2002) finds that analysts rely on simple heuristics (e.g., price-to-earnings ratio) rather than formal valuation models to derive price targets, and thus use their earnings forecasts in relatively unsophisticated ways. Asquith et al. (2005) canvass the equity valuation methods mentioned in research reports authored by "All-American" analysts and find that only about 13% of these reports refer to any variation of discounted cash flow valuation as a basis for the price target. Both studies point to the possibility that the benefits of

[1] Asquith et al. (2005, p. 276) describe a price target as a combination of several forecasts: "First, an analyst must evaluate the firm's specific cash flows and risk level. Second, an evaluation of the industry's prospects must be completed. Finally, an assessment of the macro-economic factors that affect the overall market must be undertaken."

accurate earnings forecasts are lost when sell-side analysts use unsophisticated heuristics to set their price targets. In addition, Bradshaw and Brown (2005) claim that analyst compensation increases in the accuracy of their earnings forecasts and stock recommendations but not in the quality of their price targets, so rational analysts may expend less effort on distinguishing themselves through differential price target quality. If so, price targets may serve other purposes such as to justify *ex post* analysts' buy/sell recommendations.

Our investigation extends recent work by Loh and Mian (2005), who find that analysts who issue more accurate earnings forecast also issue more profitable buy/sell stock recommendations. If analysts' stock recommendations are derived from their price targets as proscribed by textbook descriptions of the equity valuation process, the benefits of improved EPS forecast accuracy should first be evident in price target profitability. After all, price targets are a more granular measure for testing the profitability of analysts' investment opinions because price targets provide an objective indication of the dollar profit potential from trading in recommended firms' shares. However, Bradshaw and Brown (2005) find that earnings forecast accuracy is unrelated to the accuracy of analysts' price targets. They interpret this result as indicating that sell-side analysts have stronger incentives for developing accurate earnings forecasts than they do for generating profitable price targets.

Our investigation also provides new evidence on how analysts use earnings forecasts when setting price targets. *Pseudo*-price targets are constructed from analysts' earnings forecasts using two distinct valuation models: a variation of the discounted cash flow approach to equity valuation called the residual income model (RIM), and a price-earning-to-growth (PEG) heuristic (Bradshaw 2004).[2] These *pseudo*-price targets are then compared to analysts' actual price targets. Casual intuition suggests that analysts who issue more accurate earnings forecasts and who use a rigorous valuation approach like RIM will also issue superior price targets.

[2] The PEG ratio is equal to the price-to-earnings (P/E) ratio divided by the analysts' forecasted long-term earnings growth rate. Advocates of this heuristic claim that a fairly value stock should have a PEG ratio of 1.

Our empirical tests are based on a sample of 34,417 price targets provided to First Call by sell-side analysts during the calendar years 1997 through 2003. Price targets exhibit the asymmetry found in buy/sell recommendations: relatively few price targets are issued below the market price of the stock, a pattern consistent with the relative infrequency of sell recommendations. Three findings emerge from the analysis. First, we document a positive association between earnings forecast accuracy and price-target accuracy. Our results show that price targets issued by analysts with superior earnings forecasts are more likely to be met or exceeded over the ensuing 12 months than are price targets from analysts who are less able to forecast earnings. Second, there is also a positive association between earnings forecast accuracy and the profitability of trading strategies built from analysts' price targets. For example, consider a zero-investment, hedged portfolio that is long in stocks with price targets initially at least 40% above market price, and short in stocks with price targets 20% below market price. The 12-month abnormal return to this portfolio is 23.86% when analysts in the top earnings-forecast-accuracy quintile set the price targets but only -3.95% when the price targets are from analysts in the bottom forecast-accuracy quintile. Third, our results provide inconclusive evidence regarding earnings forecast accuracy, price target performance, and valuation model use.

The paper proceeds as follows. Section 2 reviews the relevant prior literature and develops our hypotheses about forecast accuracy, valuation model choice, and price target superiority. Section 3 provides details about the sample selection process, measurement issues and descriptive statistics about sample firms and analysts. The results are presented in Section 4. Concluding remarks are provided in Section 5.

## 2. Prior Research and Hypothesis Development

> "The analyst could do a more dependable and professional job of passing judgment on a common stock if he were able to determine some objective value, independent of the market quotation, with which he could compare the current price. He could then advise the investor to buy when price was substantially below value, and to sell when price exceeded value." (Graham and Dodd, 1951: 404-405)

Most sell-side analysts today respond to this dictum by disclosing price targets in their equity research reports. Asquith et al. (2005) survey equity research reports written by *Institutional Investor* "All-American" analyst team members during 1997-1999 and find that price targets are disclosed in about 73% of the reports. By comparison, all of the reports contain a summary recommendation and almost all reports also provide earnings per share (EPS) forecasts—99% for the current fiscal year and 95% for at least one subsequent year.[3] Asquith et al. (2005) find that price targets are most often associated with a 12-month horizon and are on average 33% higher than the stock's market price at the time the report is issued. Price targets below current market price are uncommon. Asquith et al. (2005) also find that over 90% of all reports containing Strong Buy or Buy recommendations include price targets, but only 11% of reports with Hold reiterations and 51% of Hold downgrades disclose price targets.

This pattern of price target disclosure is also evident in less restrictive samples of sell-side analyst reports. Bradshaw (2002) finds that price targets are disclosed in roughly two-thirds of the 103 sell-side equity reports he examines, and that the tendency to disclose a price target is greater for more favorable recommendations. Bradshaw (2002) also finds that the distribution of the ratio of the price target to market price at the date of the report is positively related to the favorableness of the recommendation, a result consistent with analysts' recommendations reflecting the disclosed price target valuations.

The direction of causality between price targets and stock recommendations is open to debate. Textbooks on equity valuation describe analysts' buy/sell recommendations as the qualitative labels assigned to the quantitative comparison of price target and market price. A Buy or Strong Buy thus indicates a stock where the price target exceeds market price, a Hold indicates a stock where price target

[3] Only 23% of the reports contain explicit EPS forecasts beyond one subsequent year, although EPS growth rate forecasts over a three to five year horizon are common.

and market price are approximately equal to one another, and a Sell indicates a stock where the price target is below market price. Bradshaw (2002), on the other hand, asserts that analysts sometimes concoct price targets *ex post* to justify their buy/sell recommendations. Asquith et al. (2005, p. 276) offer a different point of view: "Analysts might be more likely to issue highly favorable recommendations due to concerns over personal compensation, relationships with the analyzed firms' management, or their own firm's underwriting business. Price targets can be either a way for analysts to ameliorate the effects of overly optimistic reports or a part of the sales hype used to peddle stocks."

Irrespective of why they are disclosed by analysts, there is ample evidence indicating that investors consider price targets to be valuable information. Brav and Lehavy (2003) report that mean five-day abnormal returns around the release of revised prices targets range from -3.9% to +3.2%, depending on whether the report is a negative or positive price target revision. These abnormal returns compare favorably to those occurring in response to changes in analysts' buy/sell recommendations. For example, Asquith et al. (2005) find statistically significant mean five-day abnormal returns around the release of a revised buy/sell recommendation of -6.6% for downgrades and +4.5% for upgrades, and an insignificant mean reaction of 0.0% for reiterations. Both studies confirm that changes in summary earnings forecasts, stock recommendations, and price targets all provide independent information to the capital market.[4,5]

***Analysts' earnings forecast accuracy and recommendation quality***

[4] Asquith et al. (2005) find that other information contained in a report, such as the strength of the written arguments made to support an analyst's opinion, also exerts a significant influence on investor reaction to analysts' reports. The stronger the justifications provided in the report, the stronger the market's reaction to the report. When analyst justifications are included as an explanatory variable, the market still reacts strongly to changes in price targets, but the significance of earnings forecast and recommendation revisions is reduced or eliminated.

[5] Approximately half of the analyst reports in the Asquith et al. (2005) sample occur simultaneously with the release of information by the firm about earnings, dividend changes, stock splits, changes in business expectations, equity issues, debt issues, mergers and divestitures, major management changes, credit rating changes, lawsuits, and significant new contracts and/or product introductions. For this subsample, the only significant explanatory variables are the proxy for the strength of an analyst's arguments and price target revision. This suggests that for these reports, the analyst's role is to provide an interpretation of information released to the market.

Loh and Mian (2005) document a positive association between concurrent EPS forecast accuracy and buy/sell recommendation quality based on a sample of 180,921 unique analyst-firm-year combinations spanning April 1994 to March 2000. The sample is limited to firms whose fiscal years end in December to avoid the problem of non-overlapping forecasting horizons. For each year, Loh and Mian (2005) sort all analysts issuing EPS forecasts for a firm into quintiles based on the relative accuracy of their forecasts for that same year. Forecast accuracy is measured as the (unscaled) absolute difference between actual EPS (as reported by I/B/E/S) and forecasted EPS using a common cut-off date of June 30. Analysts in each concurrent accuracy quintile issue recommendations for the same set of firms.

The profitability of stock recommendations of each accuracy quintile is assessed over the 12-month period from April 1 to March 31 to maximize the overlap between the recommendation evaluation period and the annual earnings forecasting cycle. Calendar-time portfolios are constructed from the average recommendation rating of each firm within each quintile. This approach accommodates the removal of stale recommendations (issued 183 days ago and not reiterated) and days when no analyst in the quintile has an outstanding recommendation for the stock. Daily value-weighted hedged returns are computed for each accuracy quintile portfolio taking a long (short) position in stocks with a favorable (unfavorable) average recommendation. The average abnormal monthly return of a portfolio is then computed using four alternative methods: subtraction of the NYSE/AMEX/Nasdaq value-weighted index return; estimation of the CAPM regression; estimation of the Fama and French (1993) three-factor model; and estimation of a four-factor version of Fama and French (1993) that incorporates an additional momentum factor (Carhart 1997).

Loh and Mian (2005) find that the average factor-adjusted abnormal return associated with the recommendations of analysts in the highest accuracy quintile exceeds the corresponding return for analysts in the lowest accuracy quintile by 1.27% per month. The difference in portfolio performance between these two accuracy quintiles is most pronounced in the short portfolio (0.89% per month). These results indicate that the recommendations of superior earnings forecasts significantly outperform the recommendations of inferior earnings forecasters. The source of this performance differential is unclear.

Recommendation superiority in the highest accuracy quintile may indeed reflect the direct benefit of better EPS forecasts. This interpretation of the data is consistent with the notion that analysts in the highest accuracy quintile use their superior EPS forecasts as inputs to rigorous valuation models and thus produce superior price targets which then serve as the basis for their superior recommendations. Another possibility is that analysts in the highest accuracy quintile issue more timely recommendations or are just less susceptible to the well-documented optimistic bias that pervades recommendations. Our research is intended to shed further light on Loh and Mian (2005) by investigating whether analysts who produce more accurate EPS forecasts use more rigorous valuation models and produce superior price targets.

***Analysts' earnings forecast accuracy and price targets***

Asquith et al. (2005) provide evidence on the accuracy of price targets issued by "All American" analysts. In their study, a price target prediction is considered to be accurate if the analyzed firm's stock price equals the 12-month projected price target at any time during the year following the release of a report.[6] Using this definition of accuracy, approximately 54% of "All American" analysts' price targets are achieved or exceeded. Firms that achieve the price target usually overshoot it by an average of 37% during the 12 months. The remaining 46% of firms achieve an average 84% of the price target within 12 months. Asquith et al. (2005) also find that the probability of achieving a particular price target is inversely related to the level of optimism exhibited by an analyst, as measured by the projected change in a firm's stock price. For example, price targets that project a change of 0-10% and 10-20% are achieved 74.4% and 59.6% of the time, respectively. In contrast, price targets that project a change in price of 70% or more are realized in fewer than 25% of the cases observed.

Bradshaw and Brown (2005), using a sample of 95,852 12-month price targets for U.S. firms issued during 1997 through 2002, find that 45% of the price targets are met during the ensuing year. In

[6] Only twenty-two of the 818 target prices in Asquith et al. (2005) forecast a price decline, meaning that the price target is below the market price when the report is released. In these cases, an analyst is considered to be accurate and the target achieved if the stock price falls below the price target.

contrast to the concurrent forecast accuracy assignment used in Loh and Mian (2005), Bradshaw and Brown (2005) assign analysts to forecast accuracy quintiles based on their lagged annual EPS-forecast accuracy. They find no evidence of persistent differences across analysts in the accuracy of their price targets, or in the share price response to price targets issued by analysts with "good" or "bad" track records for price target attainability. More importantly, and in direct contradiction to the implications of Loh and Mian (2005), Bradshaw and Brown (2005) find that the price target accuracy of analysts who were superior EPS forecasters last year is indistinguishable from that of analysts who were inferior forecasters.[7] These results are interpreted as evidence that analysts have stronger incentives for making accurate earnings forecasts than accurate prices targets.

Prior research has reached divergent conclusions about analysts' EPS forecast accuracy, price targets performance, and recommendation profitability. Loh and Mian (2005) find that analysts who issue accurate concurrent EPS forecasts also provide more profitable investment recommendations, presumably because these more accurate earnings forecasts are used as inputs to rigorous valuation models that yield superior price targets and recommendations. In contrast, Bradshaw (2002) argues that analysts concoct their price targets whereas Bradshaw and Brown (2005) say analysts have few (if any) incentives to set accurate price targets. Our tests rely on concurrent EPS forecast accuracy to investigate the link between EPS forecast accuracy and price target superiority. We do not examine the sustainability over time of superior price target performance, the question of central interest in Bradshaw and Brown (2005).

***Analysts' valuation model choice***

Stock valuation methodologies fall into one of three categories: earnings or cash flow multiples, discounted cash flow (DCF) models, and asset multiples. Earnings or cash flow multiples include: price-to-earnings ratios; relative price-to-earnings ratios where the benchmark is other firms in the industry;

[7] Bradshaw and Brown (2005) also examine the determinants of attainable price targets and find that price targets are more likely to be met when: (i) the initial spread between target price and market price is small; (ii) market returns over the 12 month forecast horizon are higher; (iii) analysts have more experience; (iv) analysts are employed by the largest brokerage houses; and (v) stock price volatility is low.

earnings before interest, tax, depreciation, and amortization (EBITDA) multiples; and revenue multiples.[8] Multiperiod DCF models use projected free cash flows, residual income, abnormal earnings, or economic value added (EVA) derived from comprehensive financial forecasts of firm performance along with estimated discount rates. Asset multiples are market-to-book ratios, where "book" refers to either equity (i.e., net asset) book value or total asset book value.

What valuation methodologies do sell-side use when formulating price targets? Two strands of prior research are pertinent. One strand provides evidence on self-reported valuation model use based on structured content analysis of analysts' reports. For example, Demirakos, et al. (2004) examine 104 comprehensive sell-side reports issued from January 1997 to October 2001. The reports cover 26 London Stock Exchange listed companies in beverages, electronics and electrical equipment, and pharmaceuticals sectors. Rigorous multiperiod DCF valuation models (including variations of DCF like residual income) are mentioned explicitly in 50% of the reports. By contrast, theoretically inferior single-period comparative valuation techniques (e.g., earnings or sales multiples, and price-to-book or price-to-assets ratios) predominate the sample. Earnings multiples are mentioned in 89% of the reports and sales multiples are mentioned in 50% of the reports. Hybrid valuation models based on return-on-equity, cash recovery rates, and economic value added are mentioned 20.8% of the reports.

Asquith et al. (2005) provide evidence on the valuation methods mentioned in equity research reports authored by *Institutional Investor* "All-American" team members during 1997 to 1999. They find that 99% of these analysts mention use of earnings multiples (e.g., price-to-earnings ratio, EBITDA multiple, or a relative price-to-earnings ratio). Only about 13% of analysts report using DCF variations to set price targets. Notably, the DCF method is much more prevalent in recommendation downgrade reports (20.8%) than upgrades (12.7%) or reiterations (11.1%). Valuation models based on asset

[8] Penman (2004) describes the conceptual and implementation problems associated with the use of multiples for equity valuation purposes.

multiples are mentioned in 25% of all reports and another 1% of the reports do not mention any valuation method.[9]

Evidence obtained from content analyses may provide an incomplete picture of how analysts formulate price targets. As Bradshaw (2004: 27) observes: "… individual analysts who use [DCF] present value models may choose to communicate the results of their analyses in the simplest terms, excluding a detailed discussion of present value techniques (i.e., dividend assumptions, discount rates, etc.). Additionally, there are obvious proprietary costs to divulging particular methods of identifying any single security for recommended investment."

A second strand of prior research infers valuation model use by examining the extent to which sell-side analysts' recommendations or price targets are correlated with researcher-constructed estimates of intrinsic value. Drawing on a sample of 103 sell-side reports for U.S. firms, Bradshaw (2002) compares the price targets analysts' disclose in their reports with *pseudo*-price targets constructed using forward-looking PEG ratios and industry-adjusted P/E multiples that incorporate analysts' one-year and two-year earnings forecasts. PEG-based *pseudo*-price targets are highly correlated ($\rho \geq 0.50$) with disclosed price targets whereas industry P/E-based *pseudo*-price target are only moderately correlated ($\rho \leq 0.33$) with analysts' price targets. Bradshaw (2002) concludes that analysts rely on simple heuristics (i.e., single-period comparative valuation techniques) to derive their price target estimates, and thus use their earnings forecasts in a relatively unsophisticated manner. Analysts in Bradshaw's (2002) sample rarely mention the use of DCF or residual income valuation models.

In a subsequent study, Bradshaw (2004) examines whether valuation estimates based on analysts' *consensus* earnings forecasts are consistent with their *consensus* stock price recommendations. Four valuation models are considered: two specifications of the residual income model, a price-earnings-to-

[9] Only seven of the 1,126 analyst reports in the Asquith, et al. (2005) sample mentioned the use of a PEG ratio.

growth (PEG) model, and analysts' projections of long-term earnings growth.[10] The results provide little support for the notion that analysts' consensus recommendations are explained by either residual income model specification. Instead, both the PEG model and analysts' projections of long-term earnings growth best explain consensus recommendations. Analysts give the highest recommendations to growth stocks, and among growth stocks, analysts give the highest recommendations to those where the value of growth estimated by the PEG model exceeds current price. Again, the evidence suggests that analyst do not incorporate their earnings forecasts into their stock recommendations in a manner consistent with superior DCF models, but instead rely on arguably inferior valuation heuristics.[11] Notably, Bradshaw (2004) finds that investors would earn higher returns over a one-year holding period relying on present value models that incorporate analysts' earnings forecasts than on analysts' recommendations alone.[12]

Asquith et al. (2005) find no correlation between the valuation methodology mentioned by "All-American" analysts and either the market's reaction to a report's release or to price target accuracy. Among the various iterations of earnings multiples, the percentage of price targets achieved ranges from 48.4% for reports mentioning EBITDA to 55.1% for revenue multiples. The accuracy of price targets in reports mentioning DCF falls within this range, with 52.3% of the price targets achieved. Price targets in reports mentioning price-to-book models are slightly less accurate at 45.5%. Analysts are least successful in setting price targets when the report mentions a "unique" valuation method that is not used by other

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[10] The two residual income specifications differ in their assumptions regarding earnings growth at the terminal value forecast horizon. One specification assumes residual income fades to zero over time, the other assumes residual income persists. Details are provided later in Section 3 of this paper.

[11] Bradshaw (2004) finds that recommendations are (1) uncorrelated or negatively correlated with residual income valuations that predict positive future excess returns, (2) positively correlated with PEG valuations that also predict positive future excess returns, but (3) positively correlated with long-term growth estimates, which is actually a negative predictor of future excess returns.

[12] Bradshaw (2004) notes that the strongest explanatory variable for recommendations is long-term earnings growth estimates, which is a strong predictor of future negative returns. Thus, analysts favor stocks with high-growth expectations even though such expectations have already been impounded into prices. As Bradshaw (2004: 28) points out: "… the results present a conundrum: the evidence suggests that investors might as well ignore analysts' recommendations, but this conclusion stands in contrast to recent studies concluding the opposite, that analysts' recommendations are associated with future excess returns (e.g., Womack, 1996; Barber et al. 2001)." Both Womack (1996) and Barber et al. (2001) examine recommendation changes, however, not levels.

analysts or covered in most valuation textbooks. The number of analyst reports that mention these other methods, however, is quite small.

There are several messages in these findings relevant to our study. First, individual analysts often mention more than one valuation approach in describing how they arrive at their price targets and buy/sell recommendation. Second, the broad range of valuation methods analysts mention undoubtedly vary in accuracy and thus so will the resulting price targets. Prior research on inferred valuation model use (Bradshaw 2002, 2004) finds that analysts often employ heuristics that arguably yield less accurate price targets than do more rigorous multi-period DCF valuation approaches. However, these results are based on a small sample of price targets, consensus recommendations rather than the investment opinions of individual analysts, and they do not control for differences in EPS forecast accuracy as an input to the valuation process. We revisit the question of inferred valuation model use using our broad price target sample and the Loh & Mian (2005) EPS forecast accuracy framework. [13]

## 3. Sample Selection, Measurement Issues, and Descriptive Statistics

### *Sample selection and data requirements*

Several financial databases catalog and summarize sell-side analysts' EPS forecasts and stock recommendations but these databases do not compile information about analysts' price targets, valuation

[13] When properly specified, the various DCF-based multiperiod valuation models are theoretically equivalent to one another (Copeland, Koller and Murrin. 2000; Penman 2004). Implementation differences across analysts can induce differences in price target accuracy even when the same DCF valuation model is being used. The single-period comparative valuation techniques are theoretically equivalent to the multiperiod valuation models only under extremely restrictive conditions. As in Bradshaw (2002 & 2004), we limit our tests of multiperiod DCF valuation models to the residual income model (*RIM*). Francis, et al.. (2000) investigate the reliability of value estimates derived from three theoretically equivalent variations of DCF: the discounted dividend (*DIV*) model, the discounted free cash flow (*FCF*) model, and the discounted abnormal earnings (*AE*) model (also known as *RIM*). In theory, the models yield identical estimates of intrinsic value but in practice they will differ if the forecasted attributes, growth rates, or discount rates are inconsistent. Using a sample of publicly traded firms followed by *Value Line* during 1989-1993, Francis et al. (2000) find that *AE* value estimates perform significantly better than *DIV* or *FCF* value estimates. The median absolute market price prediction error for the *AE* model is about three-quarters that of the *FCF* model (30% versus 41%) and less than one-half that of the *DIV* model (30% versus 69%). Further, *AE* value estimates explain 71% of the variation in current prices compared to 51% (35%) for *DIV* (*FCF*) value estimates. The greater reliability of *AE* value estimates is driven by the ability of book value to explain a large portion of intrinsic value and, perhaps, by the greater precision and predictability of *AE* forecasts.

methodologies, or justifications for buy/sell recommendations. First Call recently made available a database containing contains roughly 766,000 individual price targets issued by analysts affiliated with 314 distinct brokerage and research firms. The First Call database identifies the brokerage firm but not the individual analyst who submits the price target so we identify individual analysts from the I/B/E/S earnings forecast detail files. Following Bradshaw and Brown (2005), we require each price target to be associated with a brokerage firm and a calendar month for which we are also able to identify the individual analyst for that brokerage firm and month from I/B/E/S. This identification process yields 223,147 price targets issued during 1007 through 2003 from analysts at 191 distinct brokerage and research firms.

We impose several additional data constraints. First, our research design takes a firm-year perspective. We limit the sample to price targets in effect at the end of the fourth month after the firm's fiscal year end and require analysts' one-year ahead and two-year ahead EPS forecasts from I/B/E/S to be issued or in effect that same month.[14] For each firm-year-analyst, we retain only the most recent price target and EPS forecasts issued prior to the end of the fourth month following the fiscal year end. This mitigates differences in forecast horizons and ensures that analysts have the same level of annual financial statement information for use as inputs to their valuation models and price targets. This further reduces the sample to 55,403 firm-year-analyst observations with both price targets and EPS forecasts.

We then obtain financial statement data from COMPUSTAT and stock price and return data from CRSP. From COMPUSTAT, we require data on common-equity book value, dividend payout, and number of common shares outstanding. We require share price to exceed $1 and to be available on CRSP three days prior to the price target issue date. We further require share price to be available 252 trading days later to compute two of our price target accuracy measures and to reduce the influence on our results of acquisitions, going-private transactions, and bankruptcies. CRSP return data is used to compute one-year buy-and-hold size-adjusted returns—corrected for delisting where applicable—starting from the

[14] An EPS forecast is considered to be "in effect" if the I/B/E/S review date is after the fourth month following the fiscal-year-end. A target price is considered "in effect" if it is the last target price forecast issued by the analyst before the end of the fourth month following the fiscal-year-end.

price target issue date. As in Frankel and Lee (1998), we delete firm-years with negative equity book values and firms with ROE or forecasted ROE greater than 100%, to facilitate construction of our RIM *pseudo*-price targets. Collectively, these constraints yield a sample comprised of 47,531 firm-year-analyst observations.

Next, we require EPS forecast accuracy quintile rankings for each firm-year-analyst in our sample. EPS forecast accuracy rankings (described below) are constructed using one-year-ahead forecasts from the entire I/B/E/S detail population. This approach ensures that our EPS forecast accuracy measure is not contaminated by any self-selection bias associated with the decision to report price targets to First Call. The following data requirements are imposed on the full I/B/E/S population in the construction of forecast accuracy rankings: (1) one-year ahead EPS forecasts are issued or in effect in the fourth month after fiscal year end and only the most recent forecast is used; (2) share price as of the last day of the fourth month after fiscal year is greater than $1; (3) the absolute value of reported EPS from I/B/E/S minus forecasted EPS (i.e., the absolute forecast error, or AFE) scaled by share price is less than 25%; and (4) there are at least five unique values of AFE each firm-year. Requirement 3 mitigates the influence of I/B/E/S data errors on our accuracy rankings. Requirement 4 ensures that each firm-year combination is represented in each forecast accuracy quintile. These restrictions reduce the available price target sample to 35,713 observations.

Finally, we remove extreme price targets from the sample by deleting the smallest and largest one percent of observations based on the ratio of price target to market price at the issue date. Following Bradshaw (2004), we also delete extreme observations that arise from implementing our valuation model tests. Specifically, observations are removed from the sample when the *pseudo*-price target to market price ratio is less than zero or greater than five. Our final sample is comprised of 34,417 firm-year-analyst price targets and EPS forecast accuracy pairs representing 3,551 individual sell-side analysts covering 2,352 distinct firms.[15]

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[15] Price targets, share prices, and inputs to the valuation models (i.e., EPS forecasts and book value per share) are adjusted for stock splits to ensure that all variables are stated on the same basis. Cumulative adjustment factors are

***Analysts price targets***

Table 1 reports descriptive statistics for the price targets in our sample. Price targets are scaled by the market price of the stock three days prior to the issue date. Consistent with the observed distribution of stock recommendations, (see, e.g., Barber et al., 2001; Jegadeesh et al., 2004 Loh and Mian 2006), we find that the distribution of the ratio of price target to market price (*TP/P*) is also skewed to the right. Values of *TP/P* greater than 1 indicate an attractive stock whereas values less than 1 indicate an unattractive stock. Table 1 shows that *TP/P* is less than or equal to 1 in roughly 7% of the sample, indicating that price targets are rarely issued when the stock is deemed unattractive. In contrast, *TP/P* ratios greater than 1.40 comprise 23% of the sample. Interestingly, Table 1 shows that the average value of *TP/P* increases from 1997 to 2000—a period generally referred to as the "tech bubble"—and then declines.

We evaluate price target accuracy over a 12-month period using four measures, the first two of which follow from Bradshaw and Brown (2005). We describe variable measurement for the case where the price target is above actual market price at the issue date, indicating that the analyst believes that market price will rise over the ensuing 12 months. [16] Our first measure (*MEET_252*) is an indicator variable equal to one if the closing price (adjusted for stock splits and stock dividends) at the end of the one-year horizon is at or above the original price target. This measure reflects the notion that price targets are forecasts of where the stock price level will be in one year.

Our second measure (*MEET_MAX*) is an indicator variable equal to one if the price target is met at any time during the 12-month horizon. This less restrictive metric captures the notion that price targets communicate analysts' beliefs that the stock price will meet or beat the price target sometime during the

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constructed from the stock split information in the First Call price target database. Not all of our variables are stated on a diluted basis. According to I/B/E/S, EPS forecast data are tracked on the same basis used by the company when it reports earnings, which for most companies is diluted EPS. It is unclear whether analysts incorporate potential dilution when formulating price targets.

[16] Directional changes in the construction of these measures are made when the price target is below market price at the issue date, indicating that the analyst believes stock price will fall over the next 12 months.

next 12 months. This metric is presumes that investors actively trade and place limit orders to sell shares once the price target is attained. Our third accuracy measure (*RET_MAX*) is the proportionate ex-dividend annualized return available to an investor who bought a share three days prior to the price target issue date and sold at the highest closing price during the next 12 months. This proportionate return is defined as:

$$RET\_MAX = \frac{P_{\max} - P}{P} \tag{1}$$

where $P_{max}$ is the highest share price attained during the 12-month horizon, $P$ is actual share price as of three days prior to the issue date. *RET_MAX* captures the maximum return available to investors who trade on the initial spread between the price target and actual share price. Finally, we calculate *RET_252*, the proportionate ex-dividend annualized return available to an investor who bought a share three days prior to the price target forecast date and sold at the end of one year:

$$RET\_MAX = \frac{P_{252} - P}{P} \tag{2}$$

***Assigning analysts to earnings forecast accuracy quintiles***

Following Loh and Mian (2005), we sort analysts into EPS forecast accuracy quintiles for each firm-year according to their unscaled absolute forecast errors:

$$AFE_{ijy} = \left| Actual_{ijy} - Forecast_{ijy} \right| \tag{3}$$

where $AFE_{ijy}$ is analyst *i*'s absolute forecast error for firm *j* in fiscal year *y*. Analysts who are less accurate at forecasting EPS either because they are more optimistic or more pessimistic would thus have larger absolute forecast errors. We do not standardize *AFE* here because we sort analysts within the same firm-year.

Each analyst then receives a rank based on *AFE*, where the analyst with the lowest *AFE* gets a rank equal to one. Analysts with the same *AFE* are assigned the same rank. Next, we subtract 0.25 from the rank and divided the resulting number by the maximum rank in the firm-year to compute a percentile score for each analyst. Loh and Mian (2005) indicate that without the subtraction of 0.25 from the rank in the numerator, the procedure allocates more analysts to the least accurate quintile compared to the most accurate quintile. Choosing to subtract a number between 0 and 1 from the rank serves to equalize the observations allocated to extreme quintiles. Finally, we sort analysts into quintiles based on the following percentile score intervals: [0, 0.2], (0.2, 0.4], (0.4, 0.6], (0.6, 0.8], and (0.8, 1]. [17]

This approach to measuring forecast accuracy has several desirable properties when compared to the price deflated absolute forecast error measure commonly used in the literature. For example, the index allows us to compare forecast accuracy across companies and years by controlling for forecast difficulty, which is likely to differ across companies and over time for a given company. However, the index also has several drawbacks. First, the index focuses on ordinal differences in forecast accuracy, ignoring cardinal differences. This may result in magnifying small differences or reducing the impact of large differences which might add noise to our tests. Second, the index limits our ability to assess the economic importance of differences in forecast accuracy. Despite these shortcomings, we feel that the relative accuracy measure is superior to the price-deflated absolute forecast error as a measure of an analyst's forecasting performance.[18]

[17] Hong and Kubik (2003) use a less restrictive approach to measure relative forecast accuracy which we may consider adopting for purposes of robustness. They first sort the analysts that cover a particular stock in a year based on their (scaled) absolute forecast error. They then assign a ranking based on this sorting; the best analyst (the one with the lowest forecast error) receives the first rank for that stock, the second best analyst receives the second rank and onward until the worst analyst receives the highest rank. If more than one analyst was equally accurate, they assign all those analysts the midpoint value of the ranks they take up (i.e., the ranks need not be integers). Under this relative ranking system, the analyst that produces the most accurate estimate of Firm A performs as well as the analyst the produces the best estimate of Firm B, regardless of the actual forecast errors of the analysts for the two firms. Ranks are then converted to a percentile score measure that corrects for differences in analyst coverage across firms. The formula for the score is:

$$Score_{ijt} = 100 - \left[ \frac{Rank - 1}{Number\ of\ \ Analysts_{jt} - 1} \right] \times 100$$

where *Number of Analysts* is the number of analysts who cover the firm in a year. If only one analyst follows a firm in a given year, a score is not calculated for that firm. An analyst with the rank of one receives a score of 100; an analyst who is the least accurate (and the only one who is least accurate) receives a score of 0. The median and mean score for a firm in a year is 50. Hong and Kubik's (2003) then define the relative forecast accuracy for a given analyst and year as the average of the analyst's forecast scores in year *t* and the two previous years for all firms covered by the analyst. Higher overall scores correspond to better analyst performance.

[18] Subsequent versions of the paper will incorporate weighted least-squares procedures to control for non-constant variance in the data. Jacob et al. (1999) note that differences in analyst following (N) induce a differential variance

Table 2 provides information about the EPS forecast accuracy of sell-side analysts that also report price targets to First Call. Panel A.1 of Table 2 reports distributional statistics describing the absolute forecast error (*AFE*) for our pooled sample of 34,417 analyst-firm-year observations. The mean unscaled *AFE* is 0.30 whereas the median unscaled AFE is 0.13. We also report two scaled forecast error measures. The average *AFE* scaled by the stock price at the end of the fourth month after the fiscal-year-end is 1.16%. The average *AFE* scaled by the absolute value of actual earnings is 27.28%. Panel A.2 of Table 2 describes signed forecast errors. On average, the analysts in our sample exhibit negative forecast errors, consistent with the well-documented end of the year optimism.

Panel B of Table 2 reports distributional statistics for AFE by accuracy quintile. Following Loh and Mian (2005), we first compute the average *AFE*, scaled by stock price, for each firm-year within each quintile. We then average the scaled AFEs across firm-years within each quintile. The last row reports the average scaled *AFE* based on the 20,655 firm-years pooled across all quintiles. The mean (median) *AFE* for quintile 1 is 0.84 (0.18) and is statistically smaller than mean (median) AFE of 1.94 (0.89) for quintile 5 (t-value = 18.97), indicating that observed differences in EPS forecast accuracy among analysts in our sample are likely to be economically meaningful.

For comparison purposes, Panel C of Table 2 reports information about the distribution of AFE by accuracy quintile for the entire I/B/E/S population. Analysts who report price targets to First Call, and thus who are included in our primary sample, produce superior EPS forecasts when compared to the population of I/B/E/S analysts. The mean and median AFE for each accuracy quintile of analysts issuing price targets (Panel B) are smaller than those in Panel C for the I/B/E/S population of analysts issuing EPS forecasts.

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in the distribution of RANK(n/N+1). To account for this potential heteroskedasticity, they re-estimate the regressions in which RANK is the dependent variable using weighted least squares with the inverse of the induced variance as weights. As shown in footnote 18 of their paper, the induced variance is equal to ((2N+1)/(6(N+1)) – ¼.

***Valuation models and pseudo-price targets***

We consider two valuation methodologies as candidates for describing of how sell-side analysts formulate price targets. One specification of the residual income (RIM) model is included in the analysis because it incorporates analysts' multi-period EPS forecasts and because prior research demonstrates its ability to identify mispriced stocks (Frankel and Lee 1998). A RIM *pseudo*-price target is estimated as the present value of expected residual income for the next five years plus a terminal value, calculated as of the end of the fifth forecast year ($TV_{t+5}$):

$$V_{RIt} = BVPS_t + \sum_{\tau=1}^{5} \frac{E_t[RI_{t+\tau}]}{(1+r)^{\tau}} + \frac{E_t[TV_{t+5}]}{(1+r)^{5}} \qquad (4)$$

where $V_{RIt}$ is the pseudo-price target at time t, BVPS is equity book value per share, RI is residual income $\left(= EPS_{t+\tau} - r * BVPS_{t+\tau-1}\right)$, EPS is earnings per share, and r is the equity cost of capital. To implement the residual income models as in Bradshaw (2004), we require one- year and two-year EPS forecasts to be available. If longer horizon forecasts are unavailable, then they are extrapolated by applying the analyst's long-term EPS growth forecast (LTG) to the most recent forecast available (e.g., $E[EPS_{t+3}]$ equal the analyst's forecast of $EPS_{t+2}$ multiplied by $(1+LTG)$). If LTG is unavailable, then earnings forecasts are imputed such that the return on equity for the latest forecast year remains constant over the forecast horizon (e.g., $E[EPS_{t+3}]$ equals the analyst's forecast of $EPS_{t+2}$ divided by $BVPS_{t+1}$, which is forecasted $ROE_{t+2}$, times $BVPS_{t+2}$). Future book values are extrapolated under a clean surplus assumption where the firm maintains its historically observed payout ratio, proxied by the payout ratio of the most recent fiscal year or the mean payout ratio over the previous three years if the prior year ratio is unreasonable (e.g., less than 0 or greater than 1). The industry discount rate ($r$) is the Fama and French (1997) industry-specific risk premium plus the risk-free rate (30-day Treasury bill yield) in effect for the month prior to the price target issue date.

Our terminal value expression allows *RI* to fade toward zero over time as a result of possible competitive pressures within the industry. To quantify the rate of fade in *RI* for a given firm, we estimate the following regression by industry using all available Compustat firms with book value, earnings before extraordinary items, and market value for at least two consecutive years during the ten years preceding the sample period:

$$RI_t = \eta + \omega RI_{t-1} + \varepsilon_t \tag{5}$$

Realized residual income is computed as annual income before extraordinary items (Compustat data item #18) cleansed of special items (item #17) assuming a 35% tax rate, less a capital charge based on Fama and French (1997) industry estimates multiplied by beginning equity book value (item #60), all divided by beginning market value (item #25 multiplied by item #199). Income is adjusted for special items to be consistent with forecasted earnings, since analysts typically do not forecast special or extraordinary items (Bradshaw and Sloan 2002). Assuming that residual income after the terminal value year is characterized by the industry-specific estimates of the fade rate (ω) yields the following terminal value:[19]

$$E_t[TV_{t+5}] = \frac{\omega}{1+r-\omega} E_t[RI_{t+5}] \tag{6}$$

The PEG ratio valuation heuristic is implemented using the two-year EPS forecast:

$$V_{PEG} = E_t\left[EPS_{t+2}\right] \times LTG \times 100 \tag{7}$$

where $V_{PEG}$ is the *pseudo*-price target and *LTG* is the analysts' projection of long-term annual earnings growth. Scaling the *pseudo*-price targets (*V*) by market price (*P*) results in a *V*/*P* ratio that provides a distribution of the relative attractiveness of stock investments.

***Descriptive statistics***

Table 3 reports descriptive statistics for our sample. Panel A provides an overview of the sample by year. The number of analyst-firm-year observations varies from a low of 1,820 in 1997 to a peak of 6,908 in 2002. The number of unique firms increases over the sample period from 719 in 1997 to 1,160 in 2002. The number of individual analysts ranges from 655 in 1997 to 1,729 in 2002.

[19] This formula is derived based on the fact that an infinite geometric series of the form $ak + ak^2 + ak^3 + \ldots$ equals $ka/(1-k)$ if $k$<1, which is true here.

Panel B describes the composition of the sample by EPS forecast accuracy quintile. Because we sort analysts into AFE quintiles based the full I/B/E/S population rather than just those analysts who also report price targets to First Call (our sample), the number of firm-year-analyst observations in our sample of analysts with price targets is not uniformly distributed across quintiles. Too few analysts in our price target sample fall into the top or bottom AFE quintile. The average number of analysts per firm-year is 1.53 for Quintile 1 and 1.44 for Quintile 5, however the median number of analysts per firm-year is one for each quintile. This same pattern holds for firm-year observations in our price target sample.

Panel C of Table 3 reports descriptive statistics for variables used in the analysis. On average, firms miss the annual consensus forecast by 30 cents per share. The mean (median) ratio of price target to market price (*TP/P*) is 1.28 (1.24). The mean (median) ratio of RIM pseudo-price target to market price ($V_{RI1}/P$) is 0.53 (0.49) indicating that RIM valuation estimates are less optimistic than are analysts' price targets. By comparison, the mean (median) ratio of PEG pseudo-price target to market price ($V_{PEG}/P$) is 1.04 (0.93) which are more in line with analysts' price targets. The lower value of the $V_{RI1}/P$ ratio relative to the $V_{PEG}/P$ ratio is consistent with Bradshaw (2004).

On average the share price meets or exceeds the price target at some time over the following year (*RET_MAX*) for 53% of analyst-firm-year observations. At the end of the one-year year period, the stock price meets or exceeds the price target for only 30% of observations (*RET_252*).[20] The maximum price over the following year represents a 44.64% average return relative to the price as of three days prior to the price target forecast date. The stock price at the end of the one-year period represents an 8.40% average return. The size-adjust return for the one-year period is 4.42%.

Table 4 reports Pearson correlation coefficients for variables used in our primary tests. Price target and market price at the report date are highly positively correlated (ρ=0.95). Price target is also significantly positively correlated with $V_{RI}$ and $V_{PEG}$. The residual income ($V_{RI}$) and PEG ratio ($V_{PEG}$) value estimates are correlated at ρ=0.71. As expected, *TP/P* is negatively correlated with the probability

[20] Bradshaw and Brown (2005) find RET_MAX and RET_252 frequencies of 45% and 24%, respectively, for their sample over a similar time period.

that the price target is met over the ensuing 12 months. On the other hand, *TP/P* is positively correlated with our return-based price target accuracy measures (*RET_MAX* and *RET_252*).

## 4. Results

### *Earnings forecast accuracy and price target accuracy*

In this section we examine if analysts who are superior at forecasting earnings also issue more accurate price target forecasts. Table 5 reports the accuracy of analysts' price targets by AFE quintile for each of our four price target accuracy measures. The first two columns of Table 5 indicates that analysts in the low EPS forecast accuracy group (Quintile 5) are slightly more optimistic in setting price targets than are analysts in the high EPS forecast accuracy group (Quintile 1). The mean *TP/P* is 1.30 for analysts in AFE quintile 5 and statistically greater than the mean *TP/P* of 1.28 for analysts in AFE quintile 1.

The remaining columns of Table 5 provide convincing evidence that analysts who are superior at forecasting EPS are also superior at formulating accurate price targets. All four price target accuracy measures decrease monotonically from the most accurate AFE quintile to the least accurate AFE quintile. The observed differences in price target accuracy between analysts in AFE quintile 1 and those in AFE quintile 5 are statistically significant at better than the 1% level. For example, 57% of the analysts in the high EPS forecast accuracy group (Quintile 1) issue price targets that are met or exceeded some time over the next 12 months (*MEET_MAX*), compared to only 49% of the analysts in the low EPS forecast accuracy group (Quintile 5). When price target performance is assessed using the market price 12 months after the price target is issued (*MEET_252*), this same pattern of price target superiority occurs. Analysts in the high EPS forecast accuracy group (Quintile 1) issue price targets that are achieved 32% of the time, compared to only 26% for analysts in the low EPS forecast accuracy group (Quintile 5). Consistent with increased frequency of achieving price targets, both stock return measures (RET_MAX and RET_252) are higher for analysts in the high EPS forecast accuracy quintile than for analysts in the low EPS forecast accuracy quintile. These return differences are both statistically and economically significant.

***Earnings forecast accuracy and price target profitability***

The results in Panel A of Table 5 indicate that analysts who are superior at forecasting EPS also issue more accurate price targets. We next examine whether price targets issued by superior analysts are more profitable after controlling for difference in price targets, market-wide price movements, and size-related differences in the composition of the firms included in each AFE accuracy quintile. We estimate the buy-and-hold size-adjusted abnormal returns (*SAR*) for the one-year window following the price target forecast date:

$$SAR_i = \left[ \prod_{t=1}^{252} (1 + r_{it}) - \prod_{t=1}^{252} (1 + r_{size,t}) \right] \tag{8}$$

where $r_{it}$ is the daily raw return for stock *i* and $r_{size,t}$ is the daily return of the NYSE/AMEX/Nasdaq size decile to which firm *i* belongs as of the beginning of the fiscal year. Returns are cumulated beginning on the price target issue date.

Panel B of Table 5 reports mean *SAR* by earnings forecast accuracy quintile and *TP/P* category. Favored stocks assigned to the highest *TP/P* category by analysts in the highest EPS forecast accuracy group (Quintile 1) earn a reliably positive size-adjusted abnormal return of 15.46%. On the other hand, stocks in this same highest TP/P categor but with price targets issued by the *least AFE accurate* analysts earn a return of -2.70%, which is statistically indistinguishable from zero.

There is no statistical difference across AFE quintiles in the returns for disfavored stocks assigned to the lowest *TP/P* category. For the second lowest *TP/P* category (i.e., *TP/P* less than 1.00 and greater than 0.80) which is also comprised of disfavored stocks, the mean abnormal return is -4.70% for analysts in the high AFE accuracy group (Quintile 1) and 14.79% for analysts in the low AFE accuracy group (Quintile 5). The difference in abnormal returns of 18.96% is statistically significant. These data suggest investors would be well served to bet against the unfavorable stock recommendations implicit in the price targets issued by analysts with inferior EPS forecasts.

The last two columns of Panel B in Table 5 report abnormal returns (and associated t-statistics) for a zero-investment hedged portfolio that is long (short) in the highest (lowest) *TP/P* category stocks in each AFE quintile. This portfolio earns statistically positive returns only when based on price targets issued by analysts with superior EPS forecasts (AFE quintiles 1 and 2). Hedged portfolio returns for the remaining AFE quintiles are not statistically distinguishable from zero. Overall, the evidence confirms that higher trading profits are associated with the price targets issued by analysts who are superior at forecasting EPS.

We also report regression tests to further explore the relation between earnings forecast accuracy and price target profitability. Specifically, we estimate the following model:

$$\begin{aligned} SAR_{ijt} &= a_0 H_{ijt} + a_1 L_{ijt} + a_2 TP/P_{ijt} * H_{ijt} + a_3 TP/P_{ijt} * L_{ijt} + a_4 RAFE_{ijt} \\ &+ a_5 TP/P_{ijt} * RAFE_{ijt} * H_{ijt} + a_6 TP/P_{ijt} * RAFE_{ijt} * L_{ijt} + \sum_{t=1997}^{2002} b_{t-1996} Y_t + e_{ijt} \end{aligned} \tag{9}$$

where $H_{ijt}$ is a dummy variable equal to 1 if *TP/P* is greater than or equal to 1 and 0 otherwise, $L_{ijt}$ is a dummy variable equal to 1 if *TP/P* is less than 1 and 0 otherwise, $RAFE_{ijt}$ is the *AFE* quintile rank (as described in Section 2) scaled to range between 0 and 1, where the most accurate analysts have a *RAFE* = 0 and the least accurate analysts have a *RAFE* = 1. We allow different intercepts and slopes on *TP/P* greater than or equal to one and *TP/P* less than one to capture structural shifts that may exist between favored and disfavored stocks. We interact *TP/P* with earnings forecast accuracy (*RAFE*).

The results obtained from this analysis are reported in Table 6. Consider the case of favored stocks; i.e., those where *TP/P* is greater than or equal to one. For the most accurate analysts (*RAFE* = 0), the intercept is -1.39 (t-value = -0.43) and the slope coefficient on *TP/P* is 8.53 (t-value = 3.46). Thus, abnormal returns are positively related to the *TP/P* ratio for the most accurate analysts. The significantly negative coefficient on *TP/P*RAFE*H* indicates that the positive relation between abnormal returns and *TP/P* becomes weaker as EPS forecast accuracy declines. In fact, for analysts who are the least accurate at forecasting EPS (*RAFE* = 1), the regression intercept is 18.38 (-1.39 + 19.77, t-value = 5.58) and the slope coefficient is -12.03 (8.53 - 20.56, t-value = 4.87). This means that abnormal returns for price target issued by the least accurate analysts actually decline as *TP/P* increases.

The intercepts and slope coefficients on *TP/P* are not significantly different from zero when the regression is restricted to disfavored stocks (i.e., those where *TP/P* is less than 1),. Overall, the regression results are consistent with those from the portfolio analysis, suggesting greater profitability for price targets issued by analysts who are superior at forecasting future EPS.

***Price targets and valuation model use***

When generating price targets, analysts might employ different valuation models to translate their earnings forecasts into price target forecasts. Our last set of tests provides evidence on analysts' valuation model use and whether analysts' valuation models vary across earnings forecast accuracy. We compute Vuong tests for relative explanatory power among the valuation metrics ($V_{RI}$, $V_{PEG}$ and *LTG*). The following univariate regression is estimated for each valuation metric:

$$TP_{ijt} = a_0 + a_1 VALUATION_{ijt} + \sum_{t=1997}^{2002} b_{t-1997} Y_t + e_{ijt} \qquad (10)$$

where *Y* is an annual indicator variable. The annual indicator variables are included to control for any changes in overall levels of price targets across the sample period.[21]

We report the results from regressing price targets on valuation estimates in Table 7. Panel A reports results for unscaled price target and valuation estimates. The data are again partitioned by EPS forecast accuracy quintile. In each quintile, $V_{RI}$ and $V_{PEG}$ have the highest overall explanatory power for price target relative to *LTG*. The difference in explanatory power of $V_{RI}$, relative to $V_{PEG}$ is significant only for analysts in the two lowest AFE quintiles, where the evidence suggests their forecasts are more consistent with residual-income valuation models

[21] Bradshaw (2004: 39) uses consensus recommendations as the independent variable in eqn. 7, and the model is estimated separately for each of the 12 fiscal months to control for systematic differences in earnings as analysts walk down their forecasts during the fiscal year. T-statistics and Voung test statistics are corrected for serial correlation in these monthly regressions.

In Panel B, we report results for price target and valuation estimates scaled by the market price as of three days prior to the price target issue date. Scaling by price produces a measure of relative profit potential and eliminates heteroskedasticity that may be present in the price level data in Panel A. We find that $V_{PEG}/P$ has significantly more explanatory power for explaining profit potential than either $V_{RI}/P$ or *LTG* regardless of AFE accuracy quintile, and that *LTG* has significantly more explanatory power than $V_{RI}/P$ for all but the lowest AFE accuracy quintile. Our results are thus consistent with Bradshaw (2004), who finds that $V_{PEG}/P$ has significantly higher explanatory power for recommendations than $V_{RI}/P$.

## 5. Summary and Conclusions

This paper investigates whether and how sell-side analysts who produce more accurate earnings forecasts also produce superior price targets. Our results indicate that analysts demonstrating superior concurrent EPS forecasting accuracy set price targets that are both more accurate and more profitable over then ensuring 12 months than do analysts with inferior forecast accuracy. With respect to inferred valuation model use, our results to date are consistent with those of Bradshaw (2002, 2004) and provide little evidence to suggest that the price target superiority of analysts in the highest EPS forecast accuracy quintile can be traced to the use of a more rigorous valuation approach. We are actively exploring the construction of more powerful tests for valuation model use..

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## Table 1. Scaled Price Targets Issued by Sell-Side Analysts from First Call.

This table reports the year-by-year descriptive statistics of the 34,417 price targets issued between January 1997 and December 2003. *TP/P* denotes the ratio of the price target to market price three days before the price target was issued. Most analysts issue price targets with a 12 month horizon, meaning that the price target is a forecast of where market price should be in one year. Values of *TP/P* less than 1 thus denote relatively unattractive stocks where as values greater than 1 denote attractive stocks. The *TP/P* categories shown in the table are ad hoc partitions. For each category, we report both the number of price targets and the percentage of total price targets issued during the year.

| Year | # of target prices | Mean *TP/P* | # of target prices by *TP/P* category: Lowest *TP/P* [0.65, 0.80] | (0.80, 1.00) | [1.00, 1.20] | (1.20, 1.40] | Highest *TP/P* (1.40, 2.51] |
|---|---|---|---|---|---|---|---|
| 1997 | 1,820 | 1.24 | 14 | 84 | 772 | 670 | 280 |
| | | | 1% | 5% | 42% | 37% | 15% |
| 1998 | 3,597 | 1.25 | 30 | 146 | 1,499 | 1383 | 539 |
| | | | 1% | 4% | 42% | 38% | 15% |
| 1999 | 4,630 | 1.30 | 44 | 238 | 1,486 | 1,732 | 1,130 |
| | | | 1% | 5% | 32% | 37% | 24% |
| 2000 | 5,501 | 1.37 | 41 | 175 | 1,224 | 2,097 | 1,964 |
| | | | 1% | 3% | 22% | 38% | 36% |
| 2001 | 5,679 | 1.32 | 66 | 298 | 1,693 | 2,015 | 1,607 |
| | | | 1% | 5% | 30% | 35% | 28% |
| 2002 | 6,908 | 1.25 | 102 | 506 | 2,712 | 2,361 | 1,227 |
| | | | 1% | 7% | 39% | 34% | 18% |
| 2003 | 6,282 | 1.24 | 93 | 602 | 2,363 | 2,058 | 1,166 |
| | | | 1% | 10% | 38% | 33% | 19% |
| Total | 34,417 | 1.28 | 390 | 2,049 | 11,749 | 12,316 | 7,913 |
| | 100% | | 1% | 6% | 34% | 36% | 23% |

## Table 2. EPS Forecast Accuracy of Sell-Side Analysts Who Also Report Price Targets to First Call.

Panels A.1 and A.2 report the absolute forecast error (*AFE*) and forecast error (*FE*), respectively, for the 34,417 analyst-firm-year observations in the sample. We first report unscaled errors. We then report errors scaled by both the price three days prior to the forecast issue date. Following Loh and Mian (2005) we arbitrarily equate the denominator to 0.5 whenever actual earnings is less than 0.5 to avoid the problem of small denominators. Panel B reports summary statistics for *AFE* scaled by price for each accuracy quintile and for the sample as a whole. EPS forecast accuracy rankings (described in more detail in the text) are constructed using one-year-ahead forecasts from the entire I/B/E/S detail population. Panel C reports statistics comparable to those in Panel B for the entire I/B/E/S population.

**Panel A.1: Overall sample *AFE* (Absolute Forecast Error)**

| | Mean | Median | St. Dev. | Min. | Max. |
|---|---|---|---|---|---|
| Unscaled ($) | 0.30 | 0.13 | 0.62 | 0.00 | 23.25 |
| Scaled by price (%) | 1.16 | 0.41 | 2.19 | 0.00 | 24.72 |
| Scaled by absolute value of actual earnings (%) | 27.28 | 10.18 | 53.67 | 0.00 | 1804.00 |

**Panel A.2: Overall sample *FE* (Forecast Error)**

| | Mean | Median | St. Dev. | Min. | Max. |
|---|---|---|---|---|---|
| Unscaled ($) | -0.13 | -0.01 | 0.68 | -23.25 | 19.82 |
| Scaled by price (%) | -0.55 | -0.04 | 2.42 | -24.59 | 24.72 |
| Scaled by absolute value of actual earnings (%) | -15.61 | -1.08 | 58.14 | -1804.00 | 388.00 |

**Panel B: *AFE* scaled by price (%) by *AFE* quintiles**

| | Mean | Median | St. Dev. | Min. | Max. |
|---|---|---|---|---|---|
| Quintile 1 (most accurate) | 0.84 | 0.18 | 1.82 | 0.00 | 23.43 |
| Quintile 2 | 1.05 | 0.36 | 1.99 | 0.00 | 23.86 |
| Quintile 3 | 1.31 | 0.49 | 2.39 | 0.00 | 24.16 |
| Quintile 4 | 1.56 | 0.64 | 2.61 | 0.01 | 24.28 |
| Quintile 5 (least accurate) | 1.94 | 0.89 | 3.04 | 0.01 | 24.72 |
| Overall | 1.31 | 0.47 | 2.41 | 0.00 | 24.72 |

**Panel C. *AFE* scaled by price (%) for the entire IBES sample**

| | # of forecasts | Mean | Median | St. Dev. | Min. | Max. |
|---|---|---|---|---|---|---|
| Quintile 1 (most accurate) | 22,962 | 1.13 | 0.25 | 2.33 | 0.00 | 23.49 |
| Quintile 2 | 30,639 | 1.50 | 0.48 | 2.69 | 0.00 | 23.87 |
| Quintile 3 | 30,316 | 1.82 | 0.65 | 3.04 | 0.00 | 24.08 |
| Quintile 4 | 28,811 | 2.19 | 0.86 | 3.47 | 0.00 | 24.40 |
| Quintile 5 (least accurate) | 24,062 | 2.89 | 1.20 | 4.26 | 0.00 | 25.00 |
| Overall | 136,790 | 1.90 | 0.65 | 3.28 | 0.00 | 25.00 |

## Table 3. Descriptive statistics.

Panel A reports sample sample descriptive statistics by year. Panel B provides descriptive statistics for the sample partitioned by *AFE* quintiles. Assignment to *AFE* accuracy quintiles is based on EPS forecast accuracy rankings (described in more detail in the text) constructed using one-year-ahead forecasts from the entire I/B/E/S detail population. Panel C reports descriptive statistics for variables used in our tests. Variable definitions are included at the end of the table.

**Panel A. Distribution of sample by fiscal years**

| | **# Distinct firms** | **# Distinct analysts** | **# Distinct brokers** | **# Firm-year-analyst obs** |
|---|---|---|---|---|
| 1997 | 719 | 655 | 43 | 1,820 |
| 1998 | 971 | 1,068 | 61 | 3,597 |
| 1999 | 1,053 | 1,271 | 76 | 4,630 |
| 2000 | 1,162 | 1,517 | 87 | 5,501 |
| 2001 | 1,145 | 1,564 | 92 | 5,679 |
| 2002 | 1,160 | 1,729 | 102 | 6,908 |
| 2003 | 1,073 | 1,596 | 122 | 6,282 |
| 1997 - 2003 | 2,352 | 3,551 | 138 | 34,417 |

**Panel B. Distribution of sample by *AFE* quintiles**

| | # of firm-year-analyst Obs. | # of firm-year-Obs. | # of Analysts per Firm-Year | | | | |
|---|---|---|---|---|---|---|---|
| | | | Mean | Median | St. Dev. | Min. | Max. |
| Quintile 1 (most accurate) | 5,942 | 3,884 | 1.53 | 1 | 0.97 | 1 | 9 |
| Quintile 2 | 8,434 | 4,687 | 1.80 | 1 | 1.27 | 1 | 14 |
| Quintile 3 | 8,156 | 4,491 | 1.82 | 1 | 1.26 | 1 | 12 |
| Quintile 4 | 7,132 | 4,273 | 1.67 | 1 | 1.13 | 1 | 14 |
| Quintile 5 (least accurate) | 4,753 | 3,320 | 1.43 | 1 | 0.78 | 1 | 7 |
| Over 5 quintiles | 34,417 | 20,655 | 4.73 | 4 | 3.41 | 1 | 23 |

**Panel C. Descriptive statistics of variables used in our tests**

| | N | Mean | Std. Dev. | Min | P10 | Median | P90 | Max |
|---|---|---|---|---|---|---|---|---|
| *AFE* | 34,417 | 0.30 | 0.62 | 0.00 | 0.02 | 0.13 | 0.72 | 23.25 |
| *AFE_Quintile* | 34,417 | 2.89 | 1.30 | 1.00 | 1.00 | 3.00 | 5.00 | 5.00 |
| *TP* | 34,417 | 41.33 | 33.77 | 1.35 | 15.00 | 35.50 | 70.00 | 893.00 |
| *P* | 34,417 | 32.87 | 25.93 | 1.05 | 11.56 | 28.54 | 57.24 | 719.69 |
| $V_{ri}$ | 34,417 | 15.86 | 12.02 | 0.00 | 4.65 | 13.34 | 29.70 | 283.14 |
| $V_{PEG}$ | 21,202 | 31.41 | 23.05 | 0.00 | 9.80 | 27.00 | 57.00 | 371.15 |
| *LTG* | 21,202 | 0.18 | 0.10 | 0.00 | 0.08 | 0.15 | 0.30 | 1.13 |
| *TP/P* | 34,417 | 1.28 | 0.25 | 0.65 | 1.03 | 1.24 | 1.60 | 2.51 |
| $V_{ri1}/P$ | 34,417 | 0.53 | 0.29 | 0.00 | 0.23 | 0.49 | 0.89 | 4.93 |
| $V_{PEG}/P$ | 21,202 | 1.04 | 0.59 | 0.00 | 0.45 | 0.93 | 1.73 | 4.93 |
| *MEET_MAX* | 34,417 | 0.53 | 0.50 | 0.00 | 0.00 | 1.00 | 1.00 | 1.00 |
| *MEET_252* | 34,417 | 0.30 | 0.46 | 0.00 | 0.00 | 0.00 | 1.00 | 1.00 |
| *RET_MAX* (%) | 34,417 | 44.64 | 75.54 | -81.19 | 2.69 | 27.23 | 95.34 | 2361.70 |
| *RET_252* (%) | 34,417 | 8.40 | 71.75 | -582.86 | -53.84 | 0.91 | 68.15 | 2113.83 |
| *SAR* (%) | 34,417 | 4.42 | 63.62 | -163.95 | -52.26 | -1.34 | 56.64 | 2442.00 |

**Variable Definition:**

| | |
|---|---|
| *AFE:* | Absolute forecast error (unscaled); |
| *AFE_Quintile:* | *AFE* Quintile ranking (following the methodology of Loh and Mian 2005); |
| *TP:* | Target Price; |
| *P:* | Share price as of three days prior to the target price forecast date; |
| $V_{ri:}$ | Value estimate based on the residual income model (five-year horizon with a fade-rate assumption); |
| $V_{PEG:}$ | Two-year-ahead forecasted *EPS* * *LTG* ; |
| *LTG:* | Forecasted long-term growth rate; |
| *MEET_MAX:* | If *TP/P* >= 1: Dummy variable equal to 1 if *TP* is met at any time during the one-year period following the target price forecast date, and 0 otherwise;<br>If *TP/P* < 1: Dummy variable equal to 1 if stock price at any time during the one-year period falls below *TP* , and 0 otherwise; |
| *MEET_252:* | If *TP/P* >= 1: Dummy variable equal to 1 if *TP* is met at the end of the one-year period following the target price forecast date, and 0 otherwise;<br>If *TP/P* < 1: Dummy variable equal to 1 if stock price at the end of the one-year period falls below *TP* , and 0 otherwise; |
| *RET_MAX* | If *TP/P* >= 1: $(P_{MAX} - P) / P$, where $P_{MAX}$ is the maximum share price during the one-year period.<br>If *TP/P* < 1: $(P - P_{MIN}) / P$, where $P_{MIN}$ is the minimum share price during the one-year period. |
| *RET_252* | If *TP/P* >= 1: $(P_{252} - P) / P$, where $P_{252}$ is share price at the end of the one-year period.<br>If *TP/P* < 1: $(P - P_{252}) / P$, where $P_{252}$ is share price at the end of the one-year period. |
| *SAR:* | Buy-and-hold size-adjusted returns cumulated from the target price forecast date. |

## Table 4. Correlation matrix (Pearson).

This table reports the Pearson correlations of variables used in our analysis. The sample size is 34,417. See Table 3 for variable definitions.

| | AFE | AFE_ Quintile | TP | P | $V_{ri1}$ | $V_{PEG}$ | LTG | TP/P | $V_{ri1}/P$ | $V_{PEG}/P$ | MEET_ MAX | MEET_ 252 | RET_ MAX | RET_ 252 | SAR |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| AFE | 1.00 | 0.14 | 0.21 | 0.21 | 0.30 | 0.24 | -0.03 | 0.05 | 0.13 | 0.06 | -0.09 | -0.08 | -0.05 | -0.09 | -0.09 |
| p-value | | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 |
| AFE_Quintile | | | 0.00 | 0.00 | 0.02 | 0.03 | 0.02 | 0.04 | 0.03 | 0.06 | -0.05 | -0.04 | -0.02 | -0.04 | -0.02 |
| | | | 0.37 | 0.72 | <.0001 | <.0001 | 0.00 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | 0.00 | <.0001 | 0.00 |
| TP | | | | 0.95 | 0.57 | 0.63 | 0.03 | 0.08 | -0.22 | -0.15 | -0.18 | -0.17 | -0.15 | -0.18 | -0.15 |
| | | | | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 |
| P | | | | | 0.64 | 0.63 | -0.03 | -0.13 | -0.22 | -0.20 | -0.11 | -0.13 | -0.18 | -0.18 | -0.14 |
| | | | | | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 |
| $V_{ri1}$ | | | | | | 0.71 | -0.29 | -0.14 | 0.39 | 0.06 | -0.08 | -0.06 | -0.20 | -0.08 | -0.07 |
| | | | | | | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 |
| $V_{PEG}$ | | | | | | | 0.16 | 0.06 | 0.07 | 0.45 | -0.14 | -0.13 | -0.12 | -0.11 | -0.09 |
| | | | | | | | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 |
| LTG | | | | | | | | 0.27 | -0.29 | 0.36 | -0.03 | -0.05 | 0.20 | 0.00 | 0.00 |
| | | | | | | | | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | 0.82 | 0.66 |
| TP/P | | | | | | | | | 0.09 | 0.34 | -0.28 | -0.18 | 0.17 | 0.06 | 0.02 |
| | | | | | | | | | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | 0.00 |
| $V_{ri1}/P$ | | | | | | | | | | 0.43 | 0.05 | 0.09 | 0.00 | 0.11 | 0.08 |
| | | | | | | | | | | <.0001 | <.0001 | <.0001 | 0.87 | <.0001 | <.0001 |
| $V_{PEG}/P$ | | | | | | | | | | | 0.00 | 0.02 | 0.16 | 0.12 | 0.09 |
| | | | | | | | | | | | 0.72 | 0.00 | <.0001 | <.0001 | <.0001 |
| MEET_MAX | | | | | | | | | | | | 0.61 | 0.37 | 0.40 | 0.32 |
| | | | | | | | | | | | | <.0001 | <.0001 | <.0001 | <.0001 |
| MEET_252 | | | | | | | | | | | | | 0.41 | 0.57 | 0.42 |
| | | | | | | | | | | | | | <.0001 | <.0001 | <.0001 |
| RET_MAX | | | | | | | | | | | | | | 0.80 | 0.74 |
| | | | | | | | | | | | | | | <.0001 | <.0001 |
| RET_252 | | | | | | | | | | | | | | | 0.76 |
| | | | | | | | | | | | | | | | <.0001 |

## Table 5. Earnings forecast accuracy, price target accuracy, and price target profitability.

Panel A reports the accuracy of analysts' price targets by *AFE* quintile for four price target accuracy measures. *MEET_MAX* is an indicator variable equal to one if the closing price is at or above the price target any time during the 12-month horizon. *MEET_252* is an indicator variable equal to one if the closing price is at or above the price target one year after the price target is issued. *RET_MAX* is the proportionate annualize return available to an investor who bought a share the days prior to the price target issue date and sold at the highest closing price during the next 12 months. *RET_252* is the proportionate annualized return available to an investor who bought a share three days prior to the price target forecast date and sold at the end of one year. Panel B reports the buy-and-hold size-adjusted abnormal return (*SAR*) by *AFE* quintile and *TP/P* category.

### Panel A: Earnings forecast accuracy and price target accuracy.

| | *TP/P* | | *MEET_MAX* | | *MEET_252* | | *RET_MAX* | | *RET_252* | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | Median | Mean | Median | Mean | Median | Mean | Median | Mean | Median |
| Quintile 1 (most accurate) | 1.28 | 1.23 | 0.57 | 1.00 | 0.32 | 0.00 | 46.73 | 28.88 | 11.62 | 3.66 |
| Quintile 2 | 1.27 | 1.23 | 0.55 | 1.00 | 0.31 | 0.00 | 45.59 | 28.06 | 10.79 | 2.65 |
| Quintile 3 | 1.28 | 1.23 | 0.54 | 1.00 | 0.30 | 0.00 | 44.32 | 27.22 | 7.77 | 0.72 |
| Quintile 4 | 1.29 | 1.24 | 0.51 | 1.00 | 0.29 | 0.00 | 43.59 | 26.37 | 6.64 | -0.73 |
| Quintile 5 (least accurate) | 1.30 | 1.25 | 0.49 | 0.00 | 0.26 | 0.00 | 42.49 | 25.08 | 3.83 | -3.61 |
| | | | | | | | | | | |
| Q5 - Q1 | 0.02 | | -0.08 | | -0.06 | | -4.24 | | -7.78 | |
| t-statistics | 4.70 | | -8.78 | | -6.96 | | -2.71 | | -5.61 | |

### Panel B: Earnings forecast accuracy and price target profitability

| | | Lowest *TP/P* | | | | Highest *TP/P* | Highest - Lowest *TP/P* | |
|---|---|---|---|---|---|---|---|---|
| | N | [0.65, 0.80] | (0.80, 1.00) | [1.00, 1.20] | (1.20, 1.40] | (1.40, 2.51] | Mean | t-statistics |
| Quintile 1 (most accurate) | 5,942 | -8.40 | -4.17 | 1.18 | 6.97 | 15.46 | 23.86 | 2.27 |
| Quintile 2 | 8,434 | -7.60 | 3.16 | 2.51 | 6.63 | 9.26 | 16.86 | 2.34 |
| Quintile 3 | 8,156 | 7.40 | 8.55 | 2.83 | 5.45 | 5.02 | -2.38 | -0.27 |
| Quintile 4 | 7,132 | 9.38 | 13.17 | 1.15 | 4.82 | 3.55 | -5.83 | -0.53 |
| Quintile 5 (least accurate) | 4,753 | 1.25 | 14.79 | 3.79 | 0.07 | -2.70 | -3.95 | -0.44 |
| | | | | | | | | |
| Q5 - Q1 | | 9.65 | 18.96 | 2.61 | -6.90 | -18.16 | | |
| t-statistics | | 1.06 | 4.00 | 1.39 | -3.33 | -5.52 | | |
| | | | | | | | | |
| Mean *SAR* over all quintiles | | -0.65 | 6.67 | 2.24 | 5.15 | 6.19 | | |
| Total N | 34,417 | 390 | 2,049 | 11,749 | 12,316 | 7,913 | | |

## Table 6. Regression test of price target profitability.

We report the results from estimating a regression of the relation between the buy-and-hold size-adjusted abnormal return (*SAR*) and the ratio of the price target to the current market price and the *AFE* quintile rank. *SAR* is calculated as the cumulated difference between the daily return for stock *i* and the daily return of the NYSE/AMEX/Nasdaq size decline to which firm *i* belongs, where the cumulating begins on the date the price target is issued. We allow different intercepts and slope coefficients for *TP/P* greater than or equal to one and *TP/P* less than one. $H_{ijt}$ is an indicator variable equal to one if *TP/P* is greater than or equal to one and zero otherwise. $L_{ijt}$ is an indicator variable equal to one if *TP/P* is less than one and zero otherwise. We also include year dummies.

$$SAR_{ijt} = a_0 H_{ijt} + a_1 L_{ijt} + a_2 TP/P_{ijt} * H_{ijt} + a_3 TP/P_{ijt} * L_{ijt} + a_4 RAFE_{ijt}$$

$$+ a_5 TP/P_{ijt} * RAFE_{ijt} * H_{ijt} + a_6 TP/P_{ijt} * RAFE_{ijt} * L_{ijt} + \sum_{t=1997}^{2002} b_{t-1996} Y_t + e_{ijt}$$

| | *H* | *L* | *TP/P * H* | *TP/P * L* | *RAFE* | *TP/P * RAFE * H* | *TP/P * RAFE * H* |
|---|---|---|---|---|---|---|---|
| Coeff. | -1.39 | -8.28 | 8.53 | 10.73 | 19.77 | -20.56 | -8.32 |
| t-statistics | -0.43 | -0.73 | 3.46 | 0.85 | 3.68 | -5.04 | -1.20 |

## Table 7. Regressions of price targets on valuation estimates.

Panel A and Panel B reports the results from regressing price targets on valuation estimates from three valuation estimates defined in Table 3. In Panel B, we scale all variable by the price three days prior to the forecast date.

**Panel A. Target price and valuation estimates are unscaled**

| Model | Intercept | $V_{ri}$ | $V_{PEG}$ | $LTG$ | Adj. R2 | N | Vuong Test (Z-statistics) |
|---|---|---|---|---|---|---|---|
| **Quintile 1 (most accurate)** | | | | | | | |
| 1 | -0.54 | 1.84 | | | 0.46 | 3,633 | $V_{ri1}$ vs $V_{PEG}$ : 1.09 |
| t-value | -0.12 | 7.44 | | | | | $V_{ri1} > LTG$ : 4.01 |
| 2 | 9.18 | | 0.90 | | 0.41 | 3633 | $V_{PEG} > LTG$ : 5.92 |
| | 2.62 | | 7.06 | | | | |
| 3 | 34.48 | | | -4.27 | 0.02 | 3,633 | |
| | 18.36 | | | -0.41 | | | |
| **Quintile 2** | | | | | | | |
| 1 | -1.64 | 1.90 | | | 0.46 | 5,241 | $V_{ri1}$ vs $V_{PEG}$ : 1.28 |
| | -0.30 | 6.39 | | | | | $V_{ri1} > LTG$ : 4.89 |
| 2 | 6.92 | | 0.95 | | 0.41 | 5,241 | $V_{PEG} > LTG$ : 7.61 |
| | 1.63 | | 6.05 | | | | |
| 3 | 34.20 | | | 8.30 | 0.02 | 5,241 | |
| | 12.40 | | | 0.57 | | | |
| **Quintile 3** | | | | | | | |
| 1 | -2.21 | 1.86 | | | 0.39 | 5,047 | $V_{ri1}$ vs $V_{PEG}$ : 0.50 |
| | -0.28 | 4.71 | | | | | $V_{ri1} > LTG$ : 5.03 |
| 2 | 6.55 | | 0.94 | | 0.38 | 5,047 | $V_{PEG} > LTG$ : 6.33 |
| | 1.26 | | 5.46 | | | | |
| 3 | 33.12 | | | 11.89 | 0.03 | 5,047 | |
| | 13.49 | | | 0.85 | | | |
| **Quintile 4** | | | | | | | |
| 1 | -0.90 | 1.85 | | | 0.53 | 4,433 | $V_{ri1} > V_{PEG}$ : 2.66 |
| | -0.17 | 6.14 | | | | | $V_{ri1} > LTG$ : 5.98 |
| 2 | 7.35 | | 0.94 | | 0.44 | 4,433 | $V_{PEG} > LTG$ : 8.06 |
| | 1.62 | | 5.26 | | | | |
| 3 | 32.13 | | | 9.03 | 0.03 | 4,433 | |
| | 13.63 | | | 0.80 | | | |
| **Quintile 5 (least accurate)** | | | | | | | |
| 1 | 0.16 | 1.75 | | | 0.58 | 2,848 | $V_{ri1} > V_{PEG}$ : 1.95 |
| | 0.04 | 7.03 | | | | | $V_{ri1} > LTG$ : 4.89 |
| 2 | 11.62 | | 0.78 | | 0.47 | 2,848 | $V_{PEG} > LTG$ : 8.11 |
| | 3.41 | | 5.57 | | | | |
| 3 | 36.24 | | | -13.94 | 0.02 | 2,848 | |
| | 18.19 | | | -2.39 | | | |

**Table 7 (Continued).**

**Panel B. Target price and valuation estimates are scaled by price**

| Model | Intercept | $V_{ri}/P$ | $V_{PEG}/P$ | $LTG$ | Adj. R2 | N | Vuong Test (Z-statistics) |
|---|---|---|---|---|---|---|---|
| **Quintile 1 (most accurate)** | | | | | | | |
| 1 | 1.17 | 0.11 | | | 0.05 | 3,633 | $V_{ri1}/P < V_{PEG}/P$: -7.55 |
| t-value | 69.25 | 4.93 | | | | | $V_{ri1}/P < LTG$: 4.07 |
| 2 | 1.12 | | 0.13 | | 0.13 | 3,633 | $V_{PEG}/P > LTG$: 2.33 |
| | 88.98 | | 14.45 | | | | |
| 3 | 1.15 | | | 0.61 | 0.10 | 3,633 | |
| | 94.60 | | | 11.13 | | | |
| **Quintile 2** | | | | | | | |
| 1 | 1.14 | 0.11 | | | 0.06 | 5,241 | $V_{ri1}/P < V_{PEG}/P$: -9.23 |
| | 81.23 | 5.62 | | | | | $V_{ri1}/P < LTG$: -4.91 |
| 2 | 1.08 | | 0.13 | | 0.16 | 5,241 | $V_{PEG}/P > LTG$: 3.90 |
| | 103.12 | | 17.24 | | | | |
| 3 | 1.13 | | | 0.58 | 0.11 | 5,241 | |
| | 119.15 | | | 13.64 | | | |
| **Quintile 3** | | | | | | | |
| 1 | 1.13 | 0.12 | | | 0.06 | 5,047 | $V_{ri1}/P < V_{PEG}/P$: -9.47 |
| | 84.96 | 7.28 | | | | | $V_{ri1}/P < LTG$: -4.11 |
| 2 | 1.08 | | 0.13 | | 0.16 | 5,047 | $V_{PEG}/P > LTG$: 3.79 |
| | 100.95 | | 17.95 | | | | |
| 3 | 1.13 | | | 0.59 | 0.11 | 5,047 | |
| | 96.89 | | | 9.97 | | | |
| **Quintile 4** | | | | | | | |
| 1 | 1.12 | 0.14 | | | 0.06 | 4,433 | $V_{ri1}/P < V_{PEG}/P$: -8.32 |
| | 73.65 | 7.13 | | | | | $V_{ri1}/P < LTG$: -3.61 |
| 2 | 1.08 | | 0.14 | | 0.15 | 4,433 | $V_{PEG}/P > LTG$: 3.76 |
| | 93.58 | | 16.98 | | | | |
| 3 | 1.13 | | | 0.61 | 0.10 | 4,433 | |
| | 107.52 | | | 12.85 | | | |
| **Quintile 5 (least accurate)** | | | | | | | |
| 1 | 1.10 | 0.17 | | | 0.06 | 2,848 | $V_{ri1}/P < V_{PEG}/P$: -6.21 |
| | 58.74 | 7.39 | | | | | $V_{ri1}/P$ vs $LTG$: -1.23 |
| 2 | 1.08 | | 0.14 | | 0.14 | 2,848 | $V_{PEG}/P > LTG$: 4.30 |
| | 76.70 | | 13.98 | | | | |
| 3 | 1.13 | | | 0.59 | 0.08 | 2,848 | |
| | 80.53 | | | 9.11 | | | |