

Valuation Model Use and the Price Target Performance of Sell-Side Equity Analysts

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Abstract

This study investigates the influence of inferred valuation model use on the investment performance of sell-side equity analysts' published price target opinions. We document the superiority of price targets as an investment tool when analysts appear to be using a rigorous stock valuation technique rather than a simple valuation heuristic. This improvement in realized 12-month stock returns is most pronounced among analysts who are also adept at formulating accurate earnings forecast, a key ingredient in both stock valuation methodologies examined here. Our results underscore the importance of both forecasting ability and valuation technique to the stock evaluation process. The potential benefits of superior earnings forecasts for price target investment performance can be lost if those forecasts are used as inputs to a flawed valuation approach.

JEL Classification: G10, G14, G24

Key Words: security analysts, earnings forecasts, price targets, earnings-based valuation models

I. Introduction

“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)

By the mid-1990s, a growing number of sell-side equity analysts had begun to disclose price targets in their published stock research reports (see Bradshaw 2002; Brav and Lehavy 2003; Asquith, Mikhail and Au 2005). Price targets presumably reflect analysts’ opinions about what a stock is truly worth and thus form the basis for their less granular Buy/Sell recommendations.¹ Despite the growing popularity of price targets and their potential to provide a more precise signal about analysts’ investment opinions, large-sample evidence on the quality of analysts’ price target opinions is limited.

Investors do consider price target revisions to be informative. The average stock price reaction at revision is comparable in magnitude to that for changes in Buy/Sell recommendations (Brav and Lehavy 2003; Asquith et al. 2005). Moreover, price target revisions contain information beyond that found in changes in analysts’ summary earnings forecasts or recommendations (Brav and Lehavy 2003; Asquith et al. 2005). However, only about 50 percent of analysts’ price targets are actually achieved during the ensuing 12 months—the most common horizon specified by analysts (Asquith et al. 2005, Bradshaw and Brown 2006). The investment returns realized from simple price target trading strategies are substantially below the *ex ante* returns implied by analysts’ price targets (Brav and Lehavy 2003).

Several factors may contribute to this relatively low incidence of price target attainability. One possibility is that price targets serve a purpose other than that envisioned by Graham and Dodd (1951). Bradshaw (2002), for example, argues that analysts sometimes concoct price targets to justify *ex post* their Buy/Sell recommendations. This *ad hoc* approach undoubtedly compromises price target quality. A second possibility is that, even when analysts derive their price targets from accepted stock valuation models, attainability is hampered by inaccurate forecasts of earnings or other firm fundamentals used as valuation model inputs. Overly optimistic earnings forecasts may thus give rise to inflated, and less

¹ Adopting the standard nomenclature, a stock the analyst believes is underpriced (i.e., one where the price target exceeds the quoted market price) will be assigned a Buy recommendation, a fairly priced stock will be assigned a Hold recommendation, and an overpriced stock will be assigned a Sell recommendation.

attainable, price targets. Evidence on how analysts' earnings forecast accuracy affects price target quality is mixed. Bradshaw and Brown (2006) find that attainability is unrelated to the (past) accuracy of analysts' earnings forecasts whereas Loh and Mian (2006) and Ertimur et al. (2007) find that analysts who issue more accurate earnings forecasts also issue more profitable Buy/Sell recommendations (a proxy for price targets).

This study departs from the prior literature and investigates a third potential contributor to low quality price targets; namely, the possibility that some sell-side analysts use unsophisticated valuation heuristics to set their price targets. Even analysts adept at formulating accurate earnings forecasts may favor the use of simple (but flawed) valuation heuristics rather than more rigorous and proven techniques.² Using a broad sample of 45,693 price targets provided to First Call by sell-side analysts during the calendar years 1997 through 2003, we implement a statistical procedure for *inferring* valuation model use from the observed correlation between analysts' price targets and researcher-constructed stock valuation estimates. We then test whether the apparent use of a more rigorous valuation approach yields higher quality price targets as measured by realized investment returns.

Our results show that substantial improvements in price target quality occur when analysts appear to use a rigorous valuation technique rather than an heuristic. This quality improvement is most pronounced among analysts who are also adept at formulating accurate earnings forecasts, a key input to the valuation models we consider. The central message from our data is that the profitability of analysts' published price targets is substantially reduced when those price targets appear to have been derived from a valuation heuristic using inferior earnings forecasts.

We present the remainder of the paper in four parts. Section 2 reviews the relevant prior literature and develops our hypotheses about valuation model use and price target quality. Section 3 provides details about the sample selection process, measurement issues, and descriptive statistics about

² For example, Value Line says that the price targets produced by its analysts are based on the analyst's projections for earnings multiplied by an estimated price/earnings ratio (see http://valueline.com/ed_vlpage.html and Brav et al. 2005).

sample firms and analysts. The results are presented in Section 4. Concluding remarks are provided in Section 5.

2. Prior Research

Asquith et al. (2005) find that price targets are disclosed in about 73 percent of the research reports authored by *Institutional Investor* “All American” analyst team members from 1997 to 1999.³ These price targets are most often associated with a 12-month horizon and are on average 33 percent higher than the stock’s market price at the time the report is published. Price targets below current market price are uncommon, and the tendency to disclose a price target is greater for more favorable stock recommendations. This price target disclosure pattern is also evident in random samples of sell-side equity research reports from this same time period (Bradshaw 2002; Brav and Lehavy 2003). Published price targets are far less prevalent before the mid-1990s.

Investors seem to believe analysts’ price target opinions are informative. Price target revisions are accompanied by a mean five-day abnormal stock return of -3.9% around downward revision announcements and +3.2% for upward revisions (Brav and Lehavy 2003). Investor reaction to price target revisions is comparable in magnitude to that for changes in Buy/Sell recommendations (Asquith et al. 2005). Both studies confirm that changes in summary earnings forecasts, stock recommendations, and price targets each provide independent value-relevant information to the capital market.⁴

This investor reaction is justified only if analysts’ price targets predict future market prices. But some have argued that published price targets may at times serve a quite different purpose. Analysts have incentives to compromise their objectivity and optimistically bias their forecasts, recommendations, and analysis (e.g., Lin and McNichols 1998; Michaely and Womack 1999; Dechow et al. 2000; Bradshaw

³ By comparison, all of the reports examined in Asquith et al. (2005) contain a summary Buy/Sell recommendation and nearly all reports also provide earnings per share (EPS) forecasts—99% for the current fiscal year and 95% for at least one subsequent year. 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.

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 sell-side reports. The stronger the justifications provided in the report, the stronger the market’s reaction to the report.

et al. 2003; Lin et al. 2003). For example, Asquith et al. (2005, p. 276) note that: “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.”

One way to gauge the predictive ability of analysts’ price targets is to determine how often they are attained. “All American” analysts’ price targets are attained 54 percent of the time during the 12 months following publication of the research report (Asquith et al. 2005).⁵ Stocks that attain the price target usually overshoot it by an average of 37 percent during the 12 months. The remaining 46 percent of stocks fall about 16 percent short of the price target at their peak over the year. Bradshaw and Brown (2006) use a comprehensive price target data set compiled by First Call to investigate the quality of 95,852 price targets for U.S. firms issued in 1997-2002. Only 45 percent of the price targets are attained in the ensuing year. They find no evidence of persistent differences among analysts in the attainability of their price targets.

Price target attainability is an incomplete measure of quality when viewed from the perspective of investors. After all, the probability of a stock attaining the price target is inversely related to the level of optimism exhibited by the analyst, as measured by the projected stock price change at publication of the research report. Put simply, a \$10 stock is much more likely over then next 12 months to attain an \$11 price target than is a \$15 price target but the realized return from doing so is vastly lower as well. We depart from this earlier emphasis on price target attainability and instead use a 12-month buy-and-hold return as our quality measure.

Our first research goal is then to document the investment returns realized by portfolios built from analysts’ price targets. If price target opinions do indeed predict future market prices, then the *ante* return implied by the price target when first published (e.g., 10% for an \$11 price target on a \$10

⁵ Less than 3% of the price targets in Asquith et al. (2005) forecast a stock price decline, meaning that the price target is below the stock’s market price when the report is published. In these cases, the prediction is considered to be attained if the stock price falls to the price target during the ensuing 12 months.

stock) should exhibit a reliably positive association with the ensuing 12-month *ex post* realized return. Evidence of a positive association between implied returns and realized returns would be consistent with the notion that price targets are credible, informative, and intended to convey analysts' opinions about the true worth of a stock rather than to serve other purposes.

Analysts' valuation model choice

Stock valuation methodologies fall into one of two broad categories: discounted cash flow (DCF) models that combine projected free cash flows or abnormal earnings derived from comprehensive financial forecasts of firm performance with estimated discount rates; and relative valuation multiples such as price-to-earnings (P/E), price-to-revenue, or price-to-book value ratios that are compared to historical norms or to other firms in the same industry.⁶ Compared to the theoretically sound DCF approach, multiples are inferior heuristics even though they may at times yield valuation estimates equal the DCF estimate.

What valuation methodologies do sell-side analysts use when formulating price targets? Despite the theoretical appeal of rigorous DCF approaches and the apparent ease with which DCF models can be implemented, many analysts seem to instead rely on heuristics. Two strands of research are pertinent.

One strand provides evidence on *self-reported* valuation model use. Demirakos, et al. (2004), for example, report that only half of the 104 comprehensive research reports in their sample of London Stock Exchange listed companies mention rigorous DCF valuation models (including variations such as residual income). Nearly all reports mention heuristics such as earnings or sales multiples, and price-to-book or price-to-assets ratios. This pattern is also evident in reports authored by *Institutional Investor* "All-American" team members. Asquith et al. (2005) find that 99 percent of these reports mention an earnings multiple (e.g., price-to-earnings) but only 13 percent mention the use of DCF or its variations.

⁶ Stock valuation methods are described, contrasted, and spreadsheet templates are provide in Damodaran (1996, 2005); Copeland, Koller, and Murrin (2000); Lundholm and Sloan (2007); and Penman (2007). These same sources discuss the shortcomings of valuation heuristics. For example, Damodaran (2005, p.754) says that the analysts' use of relative valuation multiples is often "a story telling experience; analysts' with better and more believable stores are given credit for better valuations."

DCF methods are mentioned more often when analysts issue a recommendation downgrade (20.8%) than when they reiterate (11.1%) or upgrade (12.7%) the stock.

Evidence on valuation model use obtained from content analyses of sell-side research reports may provide an incomplete picture of how analysts actually formulate their 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."

Concerns of this sort spawned a second strand of research that *infers* valuation model use from the observed correlation between analysts' price targets (or recommendations) and researcher-constructed valuation estimates. Bradshaw (2002) compares the price targets sell-side analysts disclose in a hand-collected sample of 67 research reports on U.S. firms with *pseudo*-price targets constructed from PEG ratios and industry-adjusted P/E multiples that incorporate analysts' one-year and two-year-ahead earnings forecasts.⁷ PEG-based *pseudo*-price targets are more highly correlated with actual price targets than are *pseudo*-price targets constructed from industry P/E multiples.

Bradshaw (2004) reports large sample evidence on whether valuation estimates constructed from analysts' *consensus* earnings forecasts are consistent with *consensus* Buy/Sell recommendations. Four valuation approaches are considered: two specifications of the DCF residual income model, a PEG ratio, and analysts' projections of long-term earnings growth.⁸ Analysts' price targets are not considered because of data availability limitations at the time. The results indicate that analysts seem to give their highest recommendations to growth stocks without regard to valuation, and among growth stocks, the highest recommendations are stocks favored by the PEG model. Recommendations are not well

⁷ The PEG ratio for a firm is its price-to-forward-earnings (P/E) ratio divided by a forecasted long-term earnings growth rate. PEG ratio advocates claim that a value greater than 1 constitutes a Buy signal. *Pseudo*-price targets constructed from DCF or residual income valuation models are not examined in Bradshaw (2002).

⁸ The two residual income specifications differ in their assumptions about earnings growth in the final year of the forecast horizon. One specification assumes residual income fades to zero over time; the other assumes residual income persists. Details are provided in Section 3 of this paper.

explained by *pseudo*-price targets constructed from residual income models. Notably, Bradshaw (2004) concludes that investors would earn higher returns over a one-year holding period by relying on formal DCF models that incorporate analysts' consensus earnings forecasts rather than on analysts' consensus Buy/Sell recommendations alone.

Several messages from these findings are relevant to our study. First, individual analysts often mention more than one valuation approach when describing how they arrive at their price targets and Buy/Sell recommendations. Why they do so is unclear, but one interpretation is that analysts vary in their adherence to rigorous stock valuation methodologies. Second, prior research on inferred valuation model use (Bradshaw 2002, 2004) supports the view that some analysts employ heuristics that yield less profitable price targets than do more rigorous multi-period DCF valuation approaches. However, these findings are derived from a small sample of actual price targets (Bradshaw 2002) or from consensus stock recommendations (Bradshaw 2004) that may not fully reflect the investment opinions of individual analysts.

We contribute to this research stream by providing the first large sample evidence on whether differences in inferred valuation model use by individual analysts contribute to differences in price target quality. Our research methods allow for the possibility that competing valuation approaches (e.g., DCF residual income and PEG model) sometimes yield the same price target estimate. Our tests control for potential differences in analysts' EPS forecast accuracy because earnings forecasts are inputs to the valuation models we consider.

Analysts' earnings forecast accuracy

Descriptions of the equity research process (e.g., Copeland, Koller, Murrin 2000; English 2001; Penman 2007) indicate that the quality of an analyst's stock recommendation depends on how well each of three tasks is performed: formulating accurate forecasts of earnings and other fundamentals; translating those forecasts into reliable valuation price targets; and then assigning a recommendation to the stock based on a comparison of the stock's current market price against the price target. Success at one task does not guarantee success at the others. For example, an analyst skilled at forecasting earnings

may use those superior forecasts as inputs to a flawed valuation technique thereby generating inferior price targets and recommendations. Or the advantages of accurate earnings forecasts and price targets can be diminished when investment decisions are based solely on analysts' Buy/Sell recommendations and there are inefficiencies or biases in the recommendation assignment process.

Conventional wisdom suggests that more accurate EPS forecasts will result in higher quality price targets, but there are reasons to question the strength of this predicted relation.⁹ Loh and Mian (2006) and Ertimur et al. (2007) both find that analysts who issue more accurate EPS forecasts also provide more profitable investment recommendations, but they do not identify price target superiority as the source of this profitability improvement. Bradshaw (2002) argues that analysts concoct their price targets whereas Bradshaw and Brown (2006) say analysts have few (if any) incentives to set accurate price targets. These assertions raise doubts about overall price target quality and imply a rather tenuous link between price targets and earnings forecast accuracy. Moreover, the potential benefits of superior EPS forecasts for price target quality can be lost if those forecasts are used as inputs to a flawed stock valuation model.

Our research extends Loh and Mian (2006) and Ertimur et al. (2007) by investigating whether more accurate EPS forecasts are associated with superior price targets. In so doing, we provide evidence on the extent to which inferred valuation model use amplifies or attenuates the influence of EPS forecast accuracy on price target performance. Our tests rely on concurrent EPS forecast accuracy and control for concurrent Buy/Sell recommendations.

⁹ Sustained differences exist over time in the EPS forecast accuracy of individual analysts (Stickel 1992; Sinha et al. 1997). These differences in EPS forecast accuracy can be traced to a variety of analyst, brokerage, and firm characteristics (Brown 2001; Brown and Mohammad 2001; Clement 1999; Mikhail, Walther and Willis 1997, 1999; Jacob, Lys and Neale 1999). Despite these differences, analysts' EPS forecasts remain informative for investment purposes. EPS forecasts are more informative when they are issued by analysts with a track record for accuracy, although stock prices do not appear to fully reflect the benefits of superior forecast accuracy by less well known analysts (Gleason and Lee 2003).

3. Sample Selection, Measurement Issues, and Descriptive Statistics

Data requirements

Analysts' price targets are from a First Call database of roughly 750,000 price targets issued from 1997 through 2003 by analysts affiliated with 314 distinct brokerage and stock research firms. First Call identifies the brokerage or research firm—but not the individual analyst—submitting the price target. Individual analysts are identified from the I/B/E/S earnings forecast detail file. We require each First Call price target to be associated with a U.S. company, U.S. brokerage or research firm, and calendar month for which we are also able to identify from I/B/E/S the affiliated analyst for that same company and month. We adopt a company-year perspective and limit the sample to price targets in effect at the end of the fourth month after the company's fiscal year end. We also require analysts' one-year EPS forecasts from I/B/E/S to be current that same month.¹⁰ These data restrictions yield a preliminary sample of 64,281 company-year-analyst observations from the merged First Call and I/B/E/S files.

We require share price to be available from CRSP three days prior to the First Call price target submission date. We delete firms with share prices below \$1 so that our results are not influenced by extremely large bid-ask spreads. We then remove extreme price targets by deleting the top and bottom one percent of observations based on the ratio of price target to pre-submission date share price.

Our research design groups analyst-firm-year price targets by EPS forecast accuracy quintile and the I/B/E/S detail population is used to assign quintile rankings (described below). This approach ensures that our forecast accuracy measure is not contaminated by any self-selection bias associated with the decision to report price targets to First Call. Analyst-firm-year observations from I/B/E/S are retained for purposes of forming EPS forecast accuracy quintiles if: (1) one-year ahead EPS forecasts are current in the fourth month after fiscal year end; (2) share price at that time is at least \$1; (3) the absolute forecast error scaled by share price (denoted *AFE*) is less than 25 percent; and (4) there are at least five unique

¹⁰ An EPS forecast is "current" if it is newly issued in the fourth month after the company's fiscal year-end, or was issued previously but confirmed by I/B/E/S (thus reiterated by the analyst) in that same month or later. This approach reduces the likelihood that stale EPS forecasts contaminate our sample. We also delete stale price targets (i.e., those outstanding for more than one year) because most price targets are issued with a 12-month horizon.

values of *AFE* for each firm-year.¹¹ Requirement 3 mitigates the influence of I/B/E/S data errors on our accuracy rankings. As in Loh and Mian (2006), requirement 4 ensures that each firm-year combination is represented in each EPS forecast accuracy quintile. These restrictions further reduce the price target sample to 45,693 analyst-firm-year price targets representing 4,086 individual sell-side analysts covering 2,717 distinct U.S. firms.

Analysts' price targets

Table 1 reports descriptive statistics for the price target sample. Panel A describes the frequency and average price target *ex ante* (implied) return, denoted PT/P and defined as the ratio of the analyst's price target (PT) to the stock's market price (P) three days prior to the date the price target submission date. Values of PT/P greater than 1 presumably convey the analyst's belief that the stock is an attractive investment opportunity whereas values less than 1 indicate an unattractive stock. Panel A also reports comparative statistics on the frequency with which I/B/E/S analysts issue stock recommendations or price targets each year.¹²

Several features of the price target sample are noteworthy. As indicated in panel A, price targets are available from First Call for only about one-third of the I/B/E/S analyst-firm pairs meeting our selection criteria. Price target availability increased markedly during the sample period from a low of 11 percent in 1997 to 50 percent in 2003. By contrast, Buy/Sell recommendations are available for roughly two-thirds of the I/B/E/S analyst-firm pairs, and recommendation availability peaks at 80 percent in 2003.

The average implied price target return (PT/P) for stocks in our sample is 1.32, which means that price targets when first issued exceed share prices by 32 percent on average. Mean implied return increases from 1.24 in 1997 to 1.40 in 2000—a period often referred to as the “tech bubble”—and then

¹¹ Price targets, share prices, and valuation model inputs (i.e., EPS forecasts and book value per share) are not adjusted for subsequent stock splits to avoid rounding errors common to the split adjustment process and to ensure that all variables are stated on the same basis.

¹² For purposes of this comparison, we identify an I/B/E/S EPS Forecasts sample comprised of 136,790 analyst-firm-year observations that pass the filters used to construct the price target sample. Specifically, each I/B/E/S analyst-firm-year must have a “current” one-year-ahead EPS forecast, share price is at least \$1, the absolute forecast error scaled by share price is less than 25 percent, and each firm-year must have at least 5 unique EPS forecast accuracy values. The Recommendations sample (n = 93,594) is comprised of I/B/E/S EPS Forecasts observations that also have a Buy/Sell stock recommendation outstanding in the fourth month after firm's fiscal year-end. Price targets are not required for the two comparison samples.

declines to 1.26 by 2003. Analysts' Buy/Sell recommendations exhibit a similar pattern of increasing then declining optimism. Only about 8 percent of analysts' price targets take a negative view on the stock (PT/P less than 1). This may indicate that price targets are rarely issued by analysts when the stock is deemed unattractive, or that analysts believed few covered stocks were overvalued during our sample period. Sell and strong sell recommendations are also rare.¹³

Panel B of Table 1 describes the frequency distribution of price target implied return (PT/P) for each stock recommendation category. These conditional distributions are derived from a sample of 35,241 analyst-firm-year observations where both price targets and recommendations are available. Price targets are sorted each year into five groups that range from "disfavored" stocks—where PT/P is less than 1—to "most favored" stocks comprising the top quartile of observations where PT/P is greater than 1. This sorting process preserves the natural distinction between presumably overvalued ($PT/P < 1$) and undervalued ($PT/P > 1$) stocks, and is responsive to the rather obvious asymmetry in the distribution of observed PT/P values.

The central message in panel B is that price targets and Buy/Sell recommendations are not perfect substitutes for one another as indicators of an analyst's belief about a stock's investment potential. In fact, analysts' price targets and recommendations provide discordant investment signals in a strikingly large number of cases. For example, one out of every five "strong sell" rated stocks is seemingly undervalued ($PT/P > 1$). Less than half of all "sell" rated stocks are overvalued ($PT/P < 1$). Only one out of three "strong buy" rated stocks is associated with a PT/P value in the "most favored" implied return quartile and 3% of these highly recommended stocks are seemingly overvalued ($PT/P < 1$).¹⁴ These results

¹³ The increased frequency of sell recommendations (9.8%) and pessimistic price targets (12.7%) in 2003 may be due to changes in the regulations governing stock research reports (see Barber, Lehavy, McNichols and Trueman 2006).

¹⁴ There are several reasons why the Panel B data depart from a clustering along the diagonal. Some analysts may base their stock recommendations on factors unrelated to price target's implied return. Even when analysts use price target profitability to determine their recommendations, individual brokerage houses may differ in the cutoffs used for each recommendation category. Differences in cutoff values are, however, unlikely to explain the directional mismatches (e.g., strong buy recommendations assigned to overvalued stocks) evident in the data.

echo earlier findings drawn from limited samples of price targets and recommendations (e.g., Asquith et al. 2005; Bradshaw 2002).

Inferred valuation model use

We consider two stock valuation methodologies—a residual income (RIM) specification of the DCF approach and the PEG ratio heuristic—as candidates for describing how sell-side analysts formulate price targets. The Frankel and Lee (1998) RIM specification is selected as our DCF candidate because it incorporates analysts’ multi-period EPS forecasts and because prior research demonstrates its ability to identify mispriced stocks.¹⁵ The PEG ratio is selected as our valuation heuristic because of both its reliance on analysts’ EPS forecasts and its demonstrated superiority for predicting analysts’ actual price targets when compared to industry price-earnings multiples (Bradshaw 2002). A *pseudo*-price target is constructed for each valuation approach and analyst-firm-year using the analyst’s EPS forecasts. Valuation model use is then inferred by comparing the analyst’s actual price target with these two *pseudo*-price targets. This approach, described in detail below, relies on the large sample properties of the relation between analysts’ price targets and our constructed *pseudo*-price targets.

A RIM *pseudo*-price target is estimated as the discounted 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}):

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

where V_{RIt} is the *pseudo*-price target at time t , $BVPS$ is equity book value per share, RI is residual income ($EPS_{t+\tau} - r * BVPS_{t+\tau-1}$), EPS is earnings per share, and r is the equity cost of capital or discount rate. Our RIM implementation follows Bradshaw (2004) and relies on analysts’ forecasts available at the price target issue date. We require one-year and two-year-ahead EPS forecasts and long-term EPS

¹⁵ The intellectual foundations for this specification are described in Feltham and Ohson (1995) and Ohlson (1995). All DCF-based valuation models, including RIM, are theoretically equivalent to one another (Copeland, Koller and Murrin. 2000; Penman 2007). Implementation differences across analysts can induce differences in price target quality even when the same DCF model is used. Single-period comparative valuation techniques (such as the PEG ratio) are theoretically equivalent to DCF only under very restrictive conditions.

growth estimates (LTG) to be available for each analyst-firm-year. If three-year to five-year EPS forecasts are unavailable, they are constructed by extrapolating the last available EPS forecast using the analyst's long-term EPS growth estimate; e.g., $E[EPS_{t+3}]$ is set equal to the analyst's explicit forecast of EPS_{t+2} multiplied by $(1+LTG)$. Equity book values are extrapolated by presuming that firms maintain their historical dividend payout ratios. This payout ratio is defined as the actual dividend payout ratio of the most recent fiscal year, or the mean payout 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.¹⁶

The PEG ratio valuation heuristic is implemented using the two-year-ahead EPS forecast for each analyst-firm-year:

$$V_{PEG} = E_t[EPS_{t+2}] \times LTG \times 100 \quad (2)$$

where V_{PEG} is the *pseudo*-price target and LTG is the analyst's projection of long-term annual earnings-per-share growth (Bradshaw 2004). Scaling the RIM and PEG *pseudo*-price targets (V) by share price (P) yields a V/P index of investment potential that is directly comparable to the analyst-based profitability metric PT/P . To ensure comparability, the same share price (P) is used in scaling *pseudo*-price targets and the analyst's price target.

¹⁶ To quantify the rate of fade for a given firm and year, we again follow Bradshaw (2004) and derive an empirical estimate (ω) for each Fama and French (1997) industry and sample year using all firms with the requisite data available on Compustat for at least two of the ten consecutive years prior to the sample year. For purposes of these fade rate regressions ($RI_t = \eta + \omega RI_{t-1} + \varepsilon_t$), RI is cleansed of special items and scaled by equity market value at the beginning of the year. If residual income after the terminal year is characterized by the industry/year-specific fade rate (ω), then the terminal value estimate is:

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

Our inferences regarding valuation model use are unchanged if we instead assume that RI persists in perpetuity rather than fades toward zero.

Table 2 describes the ability of RIM and PEG *pseudo*-price targets to explain cross-sectional variation in analysts' actual price targets.¹⁷ The table reports summary statistics for annual regressions of analysts' price targets on each *pseudo*-price target. Two features of the data are noteworthy. First, RIM and PEG *pseudo*-price targets both exhibit substantial explanatory power for analysts' price targets in that the adjusted R² values of the annual regressions are above 50 percent in most years. Explanatory power is moderate, however, in both 2000 and 2001. Second, the explanatory power of RIM *pseudo*-price targets exceeds that for PEG *pseudo*-price targets in every year except 2000. These results indicate that RIM *pseudo*-price targets exhibit greater descriptive validity for our sample than do *pseudo*-price targets constructed from the PEG heuristic.

Table 2 also reports summary statistics describing inferred valuation model use as measured, for a given analyst-firm-year, by $\left(\frac{|\varepsilon_{RIM}|}{|\varepsilon_{PEG}|}\right)$ where ε_{RIM} and ε_{PEG} are residuals from the *pseudo*-price target regressions. The intuition behind our use of this valuation model ratio (VMR) is straight-forward: the absolute value of the regression residual will depart from zero when the analyst's price target is not well described by the *pseudo*-price target. If RIM and PEG *pseudo*-price targets are both equally distant from the actual price target, the ratio value will be 1. Ratio values less than 1 thus favor use of RIM by the analyst whereas values greater than 1 favor use of the PEG heuristic. This approach to inferring valuation model use takes advantage of the large sample properties of the relation between analysts' price targets and our *pseudo*-price targets, and facilitates inferences about valuation model use even when there are few observations pertaining to a particular analyst. The approach also accommodates instances where the two valuation approaches yield identical *pseudo*-price targets.

¹⁷ As in Frankel and Lee (1998) and Bradshaw (2004), we eliminate observations where equity book value is negative, return-on-equity (ROE) or forecasted ROE exceeds 100%, and where the resulting *pseudo*-price target is extreme. These data restrictions along with the limited availability of analysts' two-year EPS forecasts and long-term EPS growth estimates for RIM and PEG *pseudo*-price targets reduce the sample to 21,202 analyst-firm-year observations.

Analysts' actual price targets do not exhibit a consistent pattern of deviation from RIM and PEG *pseudo*-price targets across the sample although they favor RIM in 1997 and 1998 (median VMR of 0.76 and 0.72) and favor PEG in 2000 and 2001 (median VMR of 1.16 and 1.11).

Earnings forecast accuracy

As in Loh and Mian (2006), we sort the population of I/B/E/S analysts that cover sample firms into EPS forecast accuracy quintiles for each firm-year according to their unscaled absolute forecast errors:

$$AFE_{ijy} = |Actual_{ijy} - Forecast_{ijy}| \quad (3)$$

where AFE_{ijy} is analyst i 's absolute forecast error for firm j in fiscal year y . AFE is not scaled by share price because analysts are sorted within the same firm-year. Each analyst then receives a relative rank AFE , where the analyst with the smallest AFE for that firm and year gets a rank equal to one. Analysts with the same AFE are assigned the same rank. Next, we transform each assigned rank into a percentile and sort analysts for a given firm and year into quintiles based on the percentile score.¹⁸

This approach to measuring relative EPS forecast accuracy has several desirable properties when compared to the price deflated absolute forecast error measure common to the literature. In particular, our approach facilitates comparisons of analysts' relative forecast accuracy by controlling for the inherent difficulty of the EPS forecasting task, which may vary across companies and over time for a given company. The approach also has a drawback. It ranks analysts based on ordinal differences in forecast accuracy, ignoring cardinal differences. This may add noise to our tests by muting larger forecast errors or magnifying small performance differences.

Table 3 reports descriptive statistics on the distribution of scaled absolute forecast errors (AFE) for both the population of I/B/E/S analysts who cover sample firms and the subsample who submit price targets to First Call. The mean and median scaled AFE values increase monotonically (by construction) across earnings forecast accuracy quintiles in both samples. Among analysts who also submit price

¹⁸ To construct percentiles, we subtract 0.25 from the assigned rank and divide the result by the maximum rank in the firm-year. Subtracting 0.25 from the assigned rank serves to equalize the observations allocated to extreme quintiles (Loh and Mian 2006).

targets to First Call, the mean scaled *AFE* is 0.024 (i.e., 2.4% of share price) in the least accurate earnings forecast group (Quintile 5), or three times larger than the average scaled *AFE* for the most accurate group (0.008 in Quintile 1). This divergence in scaled *AFE* suggests that differences in earnings forecast accuracy among analysts in our sample are likely to be economically meaningful.

Between-sample *t*-tests in Table 3 document the superior earnings forecast accuracy of analysts who submit price targets to First Call when compared to the larger group of I/B/E/S analysts who provide a buy/sell recommendation (but perhaps no price target) for sample firms. This result holds for each EPS forecast accuracy quintile and is not driven by differences in firm characteristics because, by construction, the same firms are represented in both analyst samples. Untabulated results also confirm that analysts who submit price targets to First Call produce superior EPS forecasts when compared to the unrestricted population of all I/B/E/S analysts.

4. Results

To assess the *realized* profitability of analysts' price target predictions, we compute 12-month characteristics-adjusted buy-and-hold abnormal common stock returns (*BHAR*) as in Daniel, Grinblatt, Titman and Wremers (1997):

$$BHAR_i = \left[\prod_{t=1}^{252} (1 + r_{it}) - \prod_{t=1}^{252} (1 + r_{C,t}) \right] \quad (4)$$

where r_{it} is the daily raw return for stock i and $r_{C,t}$ is the daily value-weighted return on the characteristics-sorted benchmark portfolio to which the firm belongs in that year.¹⁹ This approach

¹⁹ One hundred and twenty-five size, book-to-market, and momentum characteristic portfolios are formed each year. First, all NYSE, AMEX, and NASDAQ stocks are assigned to one of five size groups based on June closing equity market values and NYSE size quintiles. Within each size portfolio, firms are then sorted into five book-to-market groups using December closing values from the prior year. Within each of the 25 size and book-to-market portfolios, firms are then sorted into five return momentum portfolios based on a 12-month compounded raw return ending in May. Daily value-weighted returns to each characteristic portfolio (denoted $r_{C,t}$) are then computed as the size-weighted average of the individual daily returns for firms in each portfolio. At least six non-missing monthly returns are required to calculate return momentum and missing returns are replaced by the value-weighted market return. As in Daniel et al. (1997), raw returns are compounded through May rather than June to mitigate problems associated with the bid-ask bounce (Jegadeesh, 1990). We align earnings forecast, valuation model use, and price

controls for differences in market-wide share price movements over the investment holding period. We then compute the average *BHAR* for each of the price target implied return (*PT/T*) portfolios. If differences in the price targets analysts assign to a stock are informative for investment purposes, we should observe a pattern of increasing realized returns across these *PT/P* portfolios.

Table 4 reports average *BHAR* for the five price target portfolios. With the exception of stocks assigned to the “disfavored” group where *PT/P* is less than 1, investment performance is indeed monotonically increasing across price target portfolios. Stocks in the top (“most favored”) *PT/P* portfolio earn a statistically positive 12-month *BHAR* of 5.00% compared to the reliably negative -1.42% *BHAR* earned by “least favored” portfolio 2 stocks. By contrast, the *BHAR* for “disfavored” stocks is indistinguishable from zero even though share prices are predicted by analysts to decline.

Investment performance and valuation model use

Table 4 also provides evidence on the whether valuation model use influences the quality of analysts’ price target opinions. To investigate this question, *BHAR* are grouped by price target (*PT/P*) portfolio and valuation model use (*VMR*) quintile. Two features of the data are noteworthy. First, *BHAR* increases monotonically across price target portfolios when *VMR* implies use of a residual income valuation approach (*VMR* Quintile 1). For example, *VMR* Quintile 1 stocks belonging to the “disfavored” *PT/P* portfolio earn a 12-month abnormal return of -4.60% compared to the reliably positive 10.65% *BHAR* earned by stocks in the “most favored” *PT/T* portfolio. Second, *BHAR* does not increase across price target portfolios when *VMR* implies use of the PEG valuation approach (*VMR* Quintile 5). In fact, there is no statistical difference in the performance of stocks assigned by analysts to the “disfavored” and “most favored” *PT/T* groups in this PEG model quintile.

Collectively, the results in Table 4 are consistent with the joint hypothesis that RIM is a superior stock valuation approach for setting price targets and that *VMR* captures information about analysts’

target data by accumulating returns over a 12-month period that begins on either the price target issue date or 30 days after the fiscal year-end for price targets issued prior to that date.

actual valuation model use. The results may also reflect the unintended influence of earnings forecast accuracy as a correlated omitted variable. Earnings forecast accuracy has been shown to influence the profitability of analysts' Buy/Sell recommendations (Loh and Mian 2006; Ertimur et al. 2007), and so it is likely to also influence the profitability of analysts' price targets. Moreover, earnings forecasts are key ingredients in both the RIM and PEG approach to price target formulation. The analysis that follows provides evidence on three related issues: (1) whether earnings forecast accuracy is related to valuation model use; (2) whether accuracy influences the profitability of analysts' price targets; and (3) whether this accuracy effect (if present) subsumes the documented influence of valuation model use on price target investment performance.

Valuation model use and earnings forecast accuracy

Do analysts who are better at forecasting annual earnings also employ more rigorous valuation models when formulating price targets? Evidence on whether *inferred* valuation model use varies across earnings forecast accuracy quintiles is provided in Table 5. Analyst-firm-year observations are sorted by valuation model ratio (VMR) into quintiles each year and earnings forecast accuracy (AFE) quintiles are formed as described previously. If analysts who are the most accurate in forecasting EPS issue price targets that more closely resemble RIM rather than PEG *pseudo*-price targets, a disproportionate number of AFE Quintile 1 observations will fall into VMR Quintile 1. Similarly, if analysts who are the least accurate in forecasting EPS issue price targets that approximate PEG rather than RIM *pseudo*-price targets, the AFE Quintile 5 observations will cluster in VMR Quintile 5.

The data in panel A of Table 5 refute these predictions. Earnings forecast accuracy does not appear to be correlated with valuation model use. Instead, earnings forecast accuracy is distributed almost uniformly within a VMR quintile in that each cell contains about 20 percent of the corresponding AFE observations. This means that valuation model use is independent of earnings forecast accuracy.

Earnings forecast accuracy and price target profitability

Table 5 also reports average *BHAR* by earnings forecast accuracy (*AFE*) quintile and price target (*PT/P*) portfolio, both formed as described previously. If forecast accuracy differences influence the *ex post* profitability of analysts' price targets, investment performance should vary across *AFE* quintiles for a given *PT/P* portfolio. Moreover, price target portfolios constructed from highly accurate earnings forecasts (*AFE* Quintile 1) should outperform those where forecast accuracy is low (*AFE* Quintile 5). Both predictions are supported by the data in panel B of Table 5.

Consider, for example, the investment performance of "most favored" stocks (*PT/P* portfolio 5). Stocks in this portfolio earn, on average, a reliably positive abnormal return of 8.07% when they are associated with analysts in the top earnings forecast accuracy group (*AFE* Quintile 1). By contrast, the mean return for this *PT/P* portfolio is a reliably negative -5.45% for the bottom forecast accuracy group (*AFE* Quintile 5). Monotonically increasing returns to improved forecast accuracy are most apparent among highly favored stocks (*PT/P* portfolios 4 and 5) and disfavored stocks (*PT/P* portfolio 1, where negative returns are predicted). In fact, *AFE* Quintile 1 stocks reliably outperform the *AFE* Quintile 5 stocks in every *PT/P* portfolio as evidenced by the Q1-Q5 hedged returns.

A second message in the data is that price targets are informative for investment purposes only when forecast accuracy is relatively high (*AFE* Quintiles 1 and 2). For example, *AFE* Quintile 1 stocks in the most favored *PT/P* portfolio earn a reliably positive average annual return of 8.07% compared to an average return of -2.17% for *AFE* Quintile 1 stocks in the disfavored *PT/P* portfolio. However, when earnings forecast accuracy is quite low (*AFE* Quintile 5), analysts' price target investment opinions (*PT/P*) are inconsistent with the direction and magnitude of realized returns. *AFE* Quintile 5 stocks in the most favored *PT/P* portfolio earn a negative average abnormal return -5.45% compared to the 8.02% return for disfavored stocks. The practical implication of these findings is clear: Investors would be well served to

ignore the stock recommendations implied by price targets of analysts with inferior EPS forecasting ability.

Incremental influence of valuation model use

Regression analysis is employed to isolate the incremental effects on realized returns (*BHAR*) of differences in analysts' price target investment opinions, inferred valuation model use, and earnings forecast accuracy. We also control for Buy/Sell recommendation rating (*REC*) because analysts who are superior at forecasting EPS also issue more profitable recommendations (Loh and Mian 2006; Ertimur et al. 2007). The explanatory variables *PT/P_rank*, *VMR_rank*, *AFE_rank*, and *REC_rank* are each scaled to range between 0 and 1, and capture information about the ordinal ranking of the data.²⁰ This approach means that the regression coefficient estimates associated with each variable can be interpreted as the return to a portfolio formed on that attribute. Interaction terms are included to capture the investment performance of portfolios of specific interest; e.g., the term (*AFE_rank* x *VMR_rank*) denotes a portfolio characterized by high earnings forecast accuracy and RIM valuation model use. Calendar year fixed-effects are included but not reported.

Full sample regression results are presented in Panel A of Table 6.²¹ To facilitate interpretation of coefficient estimates, Panel B reports contrast tests for differences in portfolio performance. These tests involve linear combinations of the Panel A coefficient estimates and use two benchmark portfolios as reference points. One benchmark portfolio is comprised of analyst-firm-year observations involving stocks "most favored" by analysts' price target opinions (*PT/P_rank* = 1), the "most accurate" earnings forecasts (*AFE_rank* = 1), and use of a RIM valuation approach (*VMR_rank* = 1). This portfolio earns a

²⁰ For example, *REC_rank* equals 0 if the analyst's stock recommendation is a "strong sell" and 1 when it is a "strong buy." Similarly, *PT/P_rank* equals 1 when the price target opinion denotes as a "most favored" stock, *AFE_rank* equals 1 for the top quintile ("most accurate") EPS forecasts, and *VMR_rank* equals 1 when RIM is the inferred valuation approach.

²¹ Requiring a Buy/Sell recommendation for each analyst-firm-year reduces the sample to 16,858. Observations with studentized residuals greater than 3 in absolute value are deleted as non-representative outliers, and the statistical significance of individual regression coefficient estimates is assessed using standard errors corrected for within-firm time-series clustering of observations (Huber 1967; White 1980).

reliably positive 18.54% abnormal return over the ensuing 12 months.²² By contrast, a benchmark portfolio characterized by “disfavored” price target stocks ($PT/P_rank = 0$), the “most accurate” earnings forecasts, and RIM valuation model use earns a reliably negative -4.21% return. The returns for these two benchmark portfolios thus confirm our earlier results on the usefulness of analysts’ price targets for investment purposes when a RIM valuation approach is used and earnings forecast accuracy is high.

Panel B also documents the incremental effects on *BHAR* of changes in portfolio composition. Consider the benchmark portfolio of “most favored” *PT/P* stocks, “most accurate” earnings forecasts, and RIM valuation model use that earns a return of 18.54%. *BHAR* falls by 11.59% when the portfolio is tilted to PEG use; by 17.47% when the portfolio is tilted to the least accurate earnings forecasts; and by 23.33% when both valuation model use and earnings forecast accuracy are changed. This sharp deterioration in realized returns confirms the incremental influence of valuation model use and forecast accuracy on the investment performance of analysts’ price targets. As in our earlier findings, the *BHAR* for “most favored” *PT/P* stocks is negative (-4.79% = 18.54% - 23.33%) when analysts in the bottom EPS forecast accuracy quintile employ a PEG valuation approach in formulating their price targets.

A similar pattern of deteriorating investment performance is evident in the realized returns for stocks disfavored by analysts’ price target opinions. Recall that these stocks are seemingly overvalued ($PT/P < 1$) and thus should be sold. The benchmark portfolio abnormal return is -4.21% in Panel B for disfavored *PT/P* stocks with the “most accurate” earnings forecasts and RIM valuation model use. *BHAR* increases by 6.74% when the portfolio is tilted to PEG use; by 10.97% when the portfolio involves analysts with the “least accurate” earnings forecasts; and by 12.00% when valuation model use and earnings forecast accuracy are both changed. Investors can earn a positive 7.79% *BHAR* by purchasing

²² This return is computed as the sum of the coefficient estimates in Panel A with the exception of *REC_rank*, which we ignore. Note that the *PT/T* coefficient estimate of -12.58% in Panel A is correctly interpreted as the return to a portfolio characterized by “most favored” price target profitability ($PT/T_rank = 1$) but “least accurate” earnings forecasts ($AFE_rank = 0$) and inferred use of the PEG valuation approach ($VMR_rank = 0$). Including *REC_rank* in the contrast tests in Panel B alters the level of the benchmark portfolio but does not affect the level or significance of incremental returns for changes in portfolio composition.

(not selling short) the disfavored *PT/P* stocks in the bottom forecast accuracy quintile when price targets derived using a PEG approach.

The results in Panel C of Table 6 further document the incremental effects of earnings forecast accuracy and valuation model use on *BHAR* performance within each *PT/P* group. Benchmark portfolios reflect RIM valuation model use and the “most accurate” earnings forecasts. These data corroborate our full sample findings. For example, stocks in the top (“most favored”) *PT/P* portfolio earn a benchmark return of 37.72% while the *BHAR* for “disfavored” *PT/P* stocks is -10.74%. This pattern of investment performance underscores the value of analysts’ price targets for stock selection decisions. This value is diminished by low earnings forecast accuracy or PEG valuation model use. For example, the *BHAR* for “most favored” *PT/P* stocks falls by 11.80% when analysts’ price targets imply PEG use, and by 17.00% when analysts’ earnings forecasts are the least accurate. Similar results hold for stocks in the next most highly favored *PT/P* group. Among “disfavored” *PT/P* stocks, low forecast accuracy reduces the short position *BHAR* by 17.37% but PEG model use has little impact on investment performance.

Supplemental analysis

Timely price targets. Untabulated results show that the beginning-of-year price targets issued by *AFE* Quintile 5 analysts are 15 trading days older on average than the *AFE* Quintile 1 price targets ($p \leq 0.01$). There is no difference across *AFE* quintiles in price targets timeliness when benchmarked against EPS forecast release dates. There is also no difference in price target timeliness across valuation model (*VMR*) quintiles. Stale price targets (and thus stale earnings forecasts) are negatively related to realized returns ($p \leq 0.10$) but the Table 6 results are qualitatively unchanged when *PT* timeliness is added to the regression model. Our findings are robust to alternative abnormal stock return measures and to restricting the sample by averaging observations across analysts for a given firm and year within each *AFE* quintile.

Timely earnings forecasts. Prior research has shown that analysts’ stale earnings forecasts are less accurate than are timelier forecasts (e.g., see Brown et al. 1987; O’Brien 1998; Brown et al. 1990; Lys

and Soo 1995). Untabulated results for our sample indicate that analysts in the top earnings forecast accuracy group (*AFE* Quintile 1) issue more timely annual forecasts than do those in the bottom forecast accuracy group (Quintile 5). On average, the beginning-of-year EPS forecasts of *AFE* Quintile 5 analysts are 15 trading days older than those of *AFE* Quintile 1 analysts, a difference that is statistically significant ($p < 0.01$). This finding means that forecast timeliness may be partially responsible for difference across *AFE* quintiles in realized returns (*BHAR*).

Recommendation quality: The full sample regression results (Panel A of Table 6) provide evidence on the incremental influence of Buy/Sell recommendations on portfolio investment performance. Stocks with a “strong buy” recommendation earn 5.12% less than do “strong sell” stocks after controlling for price target opinions, earnings forecast accuracy, and inferred valuation model use. In other words, more favorable recommendations are associated with an incremental reduction in portfolio performance. This counter-intuitive result is confirmed in untabulated tests where we mimic Panel C within each earnings forecast accuracy quintile. Buy/Sell recommendations have no incremental association with realized returns for stocks in the top forecast accuracy quintile after controlling for *PT/P_rank* and inferred valuation model use. *PT/P_rank* does exhibit a strong and positive association with realized returns. This means that price targets are a more profitable investment tool than are Buy/Sell recommendations when earnings forecast accuracy is high. Buy/Sell recommendations exhibit a reliably negative incremental association with realized returns in the bottom two earnings forecast accuracy quintiles, and are insignificant in quintiles 2 and 3.

5. Summary and Conclusions

This study investigates the influence of inferred valuation model use on the investment performance of sell-side equity analysts' published price targets. Our results document that substantial improvements in price target quality occur when analysts appear to be using a rigorous residual-income valuation technique rather than a PEG valuation heuristic. This improvement in 12-month realized

returns is most pronounced among analysts who are also adept at formulating accurate earnings forecasts, a key ingredient in both stock valuation approaches. Our findings thus confirm that both departures from RIM valuation model use and inferior earnings forecasts detract from the realized returns associated with analysts' price targets. The central message from our data is that the investment value of analysts' price target opinions is reduced substantially when those price targets are seemingly derived from a valuation heuristic using inferior earnings forecasts.

Our results and conclusions are subject to several important caveats. First, the sample is concentrated in years that correspond to the "technology bubble" in share prices of firms traded on U.S. stock exchanges. Analysts' optimistic price targets and recommendations may have contributed to, or been affected by, the bubble in ways that limit the generalizability of our results to other time periods. Second, the portfolio performance documented here does not reflect the actual profits available to investors from implementable trading strategies nor was that our intent. Some (but not all) price target portfolios are formed using information about concurrent EPS forecast accuracy that is not available to investors until year-end. Third, we offer no conclusions about whether investors are efficient in their use of analysts' price targets (or Buy/Sell recommendations), or in differentiating between analysts according to their earnings forecast accuracy or valuation model use. Efficiency questions are beyond the scope of this paper.

Our results suggest several fruitful avenues for future research. One obvious avenue is to explore whether price target superiority, like recommendation profitability (Ertimur et al. 2007), is influenced by the valuation relevance of earnings and by analysts' conflicts of interest. Our understanding of analysts' valuation model use could also benefit from future research. Those of a more practical bent may wish to explore the implications of our findings for identifying profit opportunities associated with implementable trading strategies.

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Table 1. Descriptive Statistics on the Price Target Sample.

Panel A: The Frequency of EPS Forecasts, Buy/Sell Stock Recommendations, and Price Targets by Year.

This panel describes the frequency and *ex ante* implied returns of 45,693 price targets retained in the sample. Implied return (denoted PT/P) is the ratio of the price target (PT) to share price (P) three days before the price target issue date. For comparison purposes, the table also reports the frequency of EPS forecasts, Buy/Sell stock recommendations, and price targets each year in the merged I/B/E/S and First Call data set. The I/B/E/S EPS Forecasts sample is comprised of 136,790 analyst-firm-year observations that meet the sample selection requirements used in constructing the price target sample. Specifically, each I/B/E/S analyst-firm-year is required to have a “current” one-year-ahead EPS forecast in the fourth month after firm’s fiscal year-end, share price is at least \$1, the absolute forecast error scaled by share price is less than 25 percent, and each firm-year is required to have at least 5 unique values of EPS forecast accuracy. I/B/E/S analyst-firm-year observations that also have a Buy/Sell stock recommendation outstanding in the fourth month after firm’s fiscal year-end are retained in the Recommendations sample ($n = 93,594$). REC is the Buy/Sell recommendation rating (1 = Strong Buy, 5 = Strong Sell) and % Sell REC is the percentage of sell and strong sell recommendations.

Year	I/B/E/S EPS Forecasts			I/B/E/S Buy/Sell Recommendations			First Call Price Targets		
	# Firms	# Analysts	Mean analysts per firm	% w/REC	Mean REC	% Sell REC	% w/ PT	Mean PT/P	% $PT/P < 1$
1997	1,548	2,858	13.0	64%	2.16	3.2%	11%	1.24	6.6%
1998	1,583	3,182	12.5	65%	2.11	2.1%	24%	1.26	6.7%
1999	1,649	3,449	12.7	71%	2.07	1.6%	29%	1.33	7.7%
2000	1,735	3,669	12.7	69%	1.90	1.0%	34%	1.40	5.0%
2001	1,537	3,401	12.6	64%	2.02	0.9%	42%	1.38	7.2%
2002	1,480	3,306	12.3	69%	2.14	2.9%	50%	1.28	9.7%
2003	1,285	2,912	12.4	80%	2.50	9.8%	50%	1.26	12.7%
Overall	3,418	7,639	12.6	68%	2.12	3.0%	33%	1.32	8.3%

Table I. Descriptive Statistics on the Price Target Sample (continued).

Panel B: Implied Price Target Profitability (PT/P) and Buy/Sell Stock Recommendations.

This panel describes the conditional distribution of price target implied return (PT/P) by stock recommendation category for 35,241 analyst-firm-year observations where both a price target and Buy/Sell recommendation are available in the fourth month after the firm's fiscal year end. Observations with PT/P less than one are assigned to a single group of "disfavored" stocks and observations with PT/P greater than or equal to one are sorted into quartiles (group 2 through 5, where 5 denotes "most favored" stocks). For each recommendation category, we report the percentage of observations in each PT/P group.

Stock Recommendation	Price Target Implied Return Category ($PT/P < 1$ and then PT/T Quartiles)					Overall	N
	Disfavored 1	Least favored 2	3	4	Most favored 5		
Strong Sell	80%	7%	6%	4%	4%	0.5%	181
Sell	42%	30%	11%	7%	11%	2.0%	709
Hold	20%	38%	17%	13%	14%	26.0%	9,163
Buy	4%	23%	27%	24%	21%	35.3%	12,446
Strong Buy	3%	11%	24%	30%	32%	36.2%	12,742

Table 2. Inferred Valuation Model Use.

This table reports summary statistics for regression estimates of the relation between analysts' price targets (PT) and either RIM *pseudo*-price targets (V_{RIM}) or PEG *pseudo*-price targets (V_{PEG}). Also reported are descriptive statistics for valuation model use, defined as the ratio $VMR (= |\epsilon_{RIM}| / |\epsilon_{PEG}|)$, where ϵ_{RIM} is the residual from regressing PT on V_{RIM} , and ϵ_{PEG} is the residual from regressing PT on V_{PEG} . Values of VMR less than 1 denote inferred RIM model use whereas values greater than 1 denote inferred PEG model use. The limited availability of analysts' two-year-ahead EPS forecasts and long-term EPS growth estimates required for RIM and PEG *pseudo*-price targets reduces the sample to 21,202 analyst-firm-year observations. Significance levels for t-tests of the null hypothesis that the regression coefficient estimate equals zero are denoted as ***, **, and * for rejection at the 1%, 5%, and 10% level, respectively.

Year	RIM Valuation			PEG Valuation			Descriptive Statistics $VMR = \epsilon_{RIM} / \epsilon_{PEG} $			
	α	β	Adjusted R^2	α	β	Adjusted R^2	Median	25th	75th	Std. Dev.
1997	6.40***	1.95***	0.82	8.82***	0.85***	0.66	0.76	0.35	1.85	6.35
1998	5.62***	2.44***	0.75	11.61***	0.89***	0.49	0.72	0.32	1.62	6.30
1999	5.78***	2.46***	0.63	7.29***	1.17***	0.51	0.91	0.43	1.93	6.03
2000	24.71***	1.70**	0.14	13.59***	1.08***	0.24	1.16	0.70	2.00	7.02
2001	15.70***	1.94***	0.36	18.52***	0.81***	0.30	1.11	0.63	1.98	7.27
2002	11.21***	1.63***	0.62	14.64***	0.85***	0.52	1.04	0.50	2.06	7.43
2003	3.57***	1.60***	0.69	9.95***	0.85***	0.54	0.97	0.43	2.10	7.03

Table 3. Earnings Forecast Accuracy

This table describes the conditional distribution of analysts' absolute EPS forecast error (*AFE*, scaled by share price) for earnings forecast accuracy quintiles constructed from the I/B/E/S detail population for covered sample firms using one-year-ahead EPS forecasts with each firm-year required to have at least 5 unique values of *AFE*. For comparison purposes, conditional *AFE* distributions summary statistics are presented for the stock recommendation and the price target samples described in Table 1. We compute the mean scaled *AFE* across analysts for each firm-year in a given quintile, and then average across firm-years within each quintile. Significance levels for between-sample t-tests of the null hypothesis of mean equality are denoted as ***, **, and * for two-tailed rejection at the 1%, 5%, and 10% level, respectively.

Earnings Forecast Accuracy Quintile	All I/B/E/S Analysts Covering Sample Firms				I/B/E/S Analysts Providing Price Targets				Mean Difference
	Mean	Median	Std. Dev.	N	Mean	Median	Std. Dev.	N	
1 (most accurate)	0.009	0.002	0.020	16,012	0.008	0.002	0.019	7,895	0.001**
2	0.012	0.003	0.023	21,343	0.011	0.003	0.020	10,905	0.001***
3	0.015	0.005	0.026	21,037	0.013	0.005	0.024	10,482	0.001***
4	0.018	0.007	0.031	19,584	0.017	0.007	0.028	9,490	0.001***
5 (least accurate)	0.026	0.011	0.041	15,618	0.024	0.010	0.037	6,921	0.003***
Overall	0.016	0.005	0.029	93,594	0.014	0.005	0.026	45,693	0.002***

Table 4. Price Target Investment Performance and Valuation Model Use.

This table reports average 12-month buy-and-hold abnormal returns (*BHAR*) by valuation model use (*VMR*) and price target implied return (*PT/P*). Observations with *PT/P* less than one are assigned to a single profitability group (“least favored”) and observations with *PT/P* greater than or equal to one are sorted into quartiles (group 2 through 5, where 5 denotes “most favored”). Valuation model use quintiles are based on $VMR = (|\epsilon_{RIM}| / |\epsilon_{PEG}|)$ as described in Table 2. *BHAR* is computed as the difference between the one-year buy-and-hold return for firm *i* and the (size, book-to-market and momentum) characteristic portfolio return to which firm *i* belongs in that year (Daniel, et. al. 1997). Returns are accumulated over a 12-month period that begins on either the price target issue date or 30 days after the fiscal year-end for price targets issued prior to that date. Hedged portfolio returns are computed for the difference between extreme valuation model use quintiles (Q1 minus Q5) or extreme *PT/T* categories (Most Favored minus Disfavored). The limited availability of analysts’ two-year-ahead EPS forecasts and long-term EPS growth estimates required for RIM and PEG pseudo-price targets reduces the sample to 21,202 analyst-firm-year observations. Significance levels for two-tailed t-tests of the null hypothesis that portfolio returns are zero are denoted as ***, **, and * for rejection at the 1%, 5%, and 10% level, respectively.

	N	Price Target Implied Return Category (<i>PT/P</i> <1 and then <i>PT/T</i> Quartiles)					MF - D
		Disfavored 1	Least favored 2	3	4	Most favored 5	
Mean <i>BHAR</i>	21,202	2.07	-1.42**	0.18	2.20**	5.00***	3.93**
Valuation Model Use Quintile							
1 (Favors RIM)	4,237	-4.60	-2.88**	3.69*	7.57***	10.65***	15.25***
2	4,243	4.46	1.28	-0.50	2.41	4.04**	-0.42
3	4,241	2.66	-2.76**	-0.79	1.09	5.89***	3.22
4	4,243	6.72***	0.28	-0.47	-1.18	5.75**	-0.97
5 (Favors PEG)	4,238	-0.97	-3.15***	-0.85	0.84	-3.91**	-2.95
Q1 – Q5		-3.63	0.27	4.55*	6.73*	14.57***	

Table 5. Valuation Model Use and Earnings Forecast Accuracy.

Panel A: Valuation Model Use within Earnings Forecast Accuracy Quintiles.

This panel describes the conditional distribution of inferred valuation model use ($VMR = |\epsilon_{RIM}| / |\epsilon_{PEG}|$) by earnings forecast accuracy (AFE) quintile. Each cell reports the proportion of analyst-firm-year observations in a particular AFE quintile that fall into each valuation model (VMR) quintile where VMR Quintile 1 favors RIM use and Quintile 5 favors PEG use. VMR quintile assignments are determined annually. AFE quintiles are also determined annually from the I/B/E/S detail population for covered sample firms using one-year-ahead EPS forecasts with each firm-year required to have at least 5 unique values of AFE . The limited availability of analysts' two-year-ahead EPS forecasts and long-term EPS growth estimates required for RIM and PEG pseudo-price targets, and thus VMR , reduces the sample to 21,202 analyst-firm-year observations.

Earnings forecast accuracy quintile	Valuation Model Use ($VMR = \epsilon_{RIM} / \epsilon_{PEG} $) Quintiles						Overall
	N	Favors RIM			Favors PEG		
		1	2	3	4	5	
1 (most accurate)	3,633	19%	20%	20%	20%	20%	100%
2	5,241	19%	19%	21%	20%	20%	100%
3	5,047	20%	20%	20%	20%	21%	100%
4	4,433	21%	20%	19%	20%	20%	100%
5 (least accurate)	2,848	21%	21%	19%	20%	19%	100%
Mean VMR		0.21	0.59	1.00	1.72	10.14	

Table 5. Valuation Model Use and Earnings Forecast Accuracy.

Panel B: Price Target Investment Performance by Earnings Forecast Accuracy Quintile.

This panel reports average 12-month buy-and-hold abnormal returns (*BHAR*) by earnings forecast accuracy (*AFE*) quintile and each price target implied return (*PT/P*) category for the entire price target sample. *AFE* quintiles are determined annually using one-year-ahead forecasts from the I/B/E/S detail population and procedures described in the text. This quintile assignment process yields unbalanced sample sizes. Observations with *PT/P* less than one are assigned to a single profitability group (“least favored”) and observations with *PT/P* greater than or equal to one are sorted into quartiles (group 2 through 5, where 5 denotes “most favored”). *BHAR* is computed as the difference between the one-year buy-and-hold return for firm *i* and the (size, book-to-market and momentum) characteristic portfolio return to which firm *i* belongs in that year (Daniel, et. al. 1997). Returns are accumulated over a 12-month period that begins on either the price target issue date or 30 days after the fiscal year-end for price targets issued prior to that date. Hedged portfolio returns are computed for the difference between extreme *AFE* quintiles (Q1 minus Q5) or extreme *PT/T* categories (Most Favored minus Disfavored). Significance levels for two-tailed t-tests of the null hypothesis that portfolio returns are zero are denoted as ^{***}, ^{**}, and ^{*} for rejection at the 1%, 5%, and 10% level, respectively.

	Price Target Implied Return Category (<i>PT/P</i> <1 and then <i>PT/T</i> Quartiles)						MF - D
	N	Disfavored 1	Least favored 2	3	4	Most Favored 5	
Earnings Forecast Accuracy Quintile							
1 (most accurate)	7,659	-2.17	-2.37 ^{***}	1.67	5.11 ^{***}	8.07 ^{***}	10.24 ^{***}
2	10,665	-2.56 ^{**}	-1.48 ^{**}	1.10	3.75 ^{***}	6.04 ^{***}	8.60 ^{***}
3	10,251	3.73 [*]	-0.95	-0.58	3.08 ^{***}	2.37 [*]	-1.36
4	9,271	6.85 ^{***}	-1.80 ^{**}	-0.94	1.49	1.39	-5.46
5 (least accurate)	6,740	8.02 ^{***}	1.76	-2.52 ^{**}	-1.46	-5.45 ^{***}	-13.47 ^{***}
Q1- Q5		-10.19 ^{***}	-4.12 ^{**}	4.18 ^{**}	6.57 ^{***}	13.52 ^{***}	
Mean <i>BHAR</i> over all quintiles		2.35 ^{**}	-1.13 ^{***}	-0.14	2.58 ^{***}	2.57 ^{***}	

Table 6. The Incremental Effects on Price Target Investment Performance of Valuation Model Use and Earnings Forecast Accuracy.

This table reports the results obtained from buy-and-hold annual abnormal return (*BHAR*) regression tests of the incremental effects of valuation model use (*VMR*) and earnings forecast accuracy (*AFE*) after controlling for price target implied return (*PT/P*) and Buy/Sell stock recommendation rating. *BHAR* is computed as the difference between the one-year buy-and-hold return for firm *i* and the (size, book-to-market and momentum) characteristic portfolio return to which firm *i* belongs in that year (Daniel, et. al. 1997). Returns are accumulated over a 12-month period that begins on either the price target issue date or 30 days after the fiscal year-end for price targets issued prior to that date. The variables *PT/P_rank*, *REC_rank*, *AFE_rank*, and *VMR_rank* are scaled to range between 0 and 1, and capture information about the ordinal ranking of the data. Specifically, *VMR_rank* equals 1 when the data imply use of the RIM valuation approach, *AFE_rank* is 1 for the quintile of most accurate EPS forecasts, *REC_rank* is 0 when the analyst’s recommendation is a “strong sell” and 1 when it is a “strong buy”, and *PT/P_rank* is 1 for “most favored” stocks. Year fixed-effects are included but not reported. The availability of Buy/Sell recommendations limits the sample to 16,858 analyst-firm-years. Observations with studentized residuals greater than 3 in absolute value are deleted in each regression. Significance levels for t-tests of the null hypothesis that the regression coefficient is zero are denoted as ^{***}, ^{**}, and ^{*} for rejection at the 1%, 5%, and 10% level, respectively.

Panel A: Full Sample Regression.

Coefficient Estimates										
Intercept	<i>PT/P_rank</i>	<i>REC_rank</i>	<i>AFE_rank</i>	<i>VMR_rank</i>	<i>PT/P_rank</i> <i>x AFE_rank</i>	<i>PT/P_rank</i> <i>x VMR_rank</i>	<i>AFE_rank</i> <i>x VMR_rank</i>	<i>PT/P_rank</i> <i>x AFE_rank</i> <i>x VMR_rank</i>	Adjusted R ²	N
7.79 ^{***}	-12.58 ^{***}	-5.12 ^{**}	-5.26 [*]	-1.03	17.00 ^{***}	6.89	-5.71	11.44	1.9%	16,858

Table 6. The Incremental Effects on Price Target Investment Performance of Valuation Model Use and Earnings Forecast Accuracy.

Panel B: Portfolio Return Estimates from the Full Sample Regression Model

This panel reports buy-and-hold abnormal returns (*BHAR*) to benchmark portfolios and the incremental returns associated with changes in the composition of the benchmark portfolios. Portfolio returns and incremental returns are computed as linear combinations of the full sample regression (Panel A) coefficient estimates with the exception of *REC_rank*, which we ignore. Significance levels for F-tests of the null hypothesis that the portfolio return or incremental return is zero are denoted as ^{***}, ^{**}, and ^{*} for rejection at the 1%, 5%, and 10% level, respectively.

Benchmark Portfolio	<i>BHAR</i>	Incremental <i>BHAR</i> from Change in Portfolio Composition		
		<i>VMR</i> = PEG	<i>AFE</i> = Least accurate	<i>VM</i> = PEG and <i>AFE</i> = Least accurate
<i>PT/P</i> = Most favored, <i>AFE</i> = Most accurate, <i>VMR</i> = RIM	18.54 ^{***}	-11.59 ^{**}	-17.47 ^{***}	-23.33 ^{***}
<i>PT/P</i> = Disfavored, <i>AFE</i> = Most accurate, <i>VMR</i> = RIM	-4.21 ^{**}	6.74 ^{**}	10.97 ^{***}	12.00 ^{***}

Panel C: Portfolio Return Estimates from *PT/P* Category Regression Models

Portfolio returns and incremental portfolio returns are computed as linear combinations of the regression coefficient estimates obtained for each *PT/P* group, consistent with panel B. Significance levels for F-tests of the null hypothesis that the portfolio return or incremental return is zero are denoted as ^{***}, ^{**}, and ^{*} for rejection at the 1%, 5%, and 10% level, respectively.

Benchmark Portfolio	<i>PT/T</i> Group	<i>BHAR</i>	Incremental <i>BHAR</i> from Change in Portfolio Composition		
			<i>VMR</i> = PEG	<i>AFE</i> = Least accurate	<i>VMR</i> = PEG and <i>AFE</i> = Least accurate
<i>VMR</i> = RIM, <i>AFE</i> = Most Accurate	1 (Most favored)	37.72 ^{***}	-11.80 ^{***}	-17.00 ^{***}	-21.38 ^{***}
<i>VMR</i> = RIM, <i>AFE</i> = Most Accurate	2	22.59 ^{***}	-8.84 ^{***}	-9.70 ^{***}	-16.02 ^{***}
<i>VMR</i> = RIM, <i>AFE</i> = Most Accurate	3	-3.71	1.82	-1.65	-5.85 ^{**}
<i>VMR</i> = RIM, <i>AFE</i> = Most Accurate	4 (Least favored)	-1.29	0.56	-1.69	1.49
<i>VMR</i> = RIM, <i>AFE</i> = Most Accurate	5 (Disfavored)	-10.74 ^{**}	6.16	17.37 ^{***}	18.87 ^{***}