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. There is limited and inconclusive evidence on how analysts' price targets are determined and on their value for investment decisions. Using a broad sample of 45,693 price targets provided to First Call by sell-side analysts during 1997 through 2003, we first show that price targets have investment value because they predict future stock returns. Next, we develop and implement an innovative large-sample procedure for *inferring* valuation model use from the observed correlation between analysts' price targets and two researcher-constructed stock valuation estimates that differ in simplicity and rigor. Reliance on a less rigorous valuation model may diminish the investment advantage associated with an analyst's more accurate earnings forecasts but it may also mitigate the disadvantage of less accurate forecasts. We test whether the apparent use of a more rigorous valuation technique yields higher quality price targets as measured by realized investment returns over a 12-month horizon, controlling for possible differences in earnings forecast accuracy. The central message from our data is that price targets exhibit superior investment performance when analysts appear to be using a fundamental residual income (RIM) stock valuation technique rather than a simple price-earnings-growth (PEG) valuation heuristic. This investment advantage is reduced when analysts' earnings forecasts are inaccurate. Our results underscore the importance of valuation model choice to analyst's stock investment evaluation process.

JEL Classification: G10, G14, G24

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

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1. 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: 404-5)

By the mid-1990s, a growing number of sell-side equity analysts had begun to disclose price targets in their published stock research reports.[1] Price targets are presumably intended to convey analysts' opinions about what a stock is truly worth and thus form the basis for their less granular Buy/Sell recommendations. 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, Mikhail, and Au 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, less than 50 percent of analysts' price targets are actually attained during the ensuing 12 months—the most common horizon analysts specify (Asquith et al. 2005; Bradshaw and Brown 2006). Additionally, the

[1] Among the roughly 378,000 stock research reports published between July 1982 and December 1996 and available from the INVESTEXT© archive, we find from text searches that only 9 percent mention price targets. The frequency of price targets in published stock research reports increases to 32.8 percent for the period January 1997 to December 2003 (our sample period), and 42.8 percent after December 2003. As described later in the paper, we draw our price target sample from the First Call electronic data files rather than hand-collect price targets from INVESTEXT© stock research reports. Individual analysts' price targets published from 1999 on are now also available through I/B/E/S.

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).

Prior research has identified two factors that may explain why analysts' published price targets are of limited value as investment signals. 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. Such *ad hoc* departures from traditional valuation methods undoubtedly compromise price target quality. A second possibility is that, even when analysts derive their price targets using accepted stock valuation techniques, price target quality is compromised by inaccurate forecasts of earnings, cash flows, or other firm fundamentals that serve as valuation model inputs. Overly optimistic earnings forecasts, for example, may give rise to inflated price targets that exaggerate potential investment returns. The available evidence on how analysts' earnings forecast accuracy affects price target quality is scant and varies with research design choices. Bradshaw and Brown (2006) find that the *past* accuracy of analysts' earnings forecasts is unrelated to price target attainability. Loh and Mian (2006) and Ertimur, Sunder, and Sunder (2007) find that analysts who issue more accurate *contemporaneous* earnings forecasts also issue more profitable Buy/Sell recommendations (a proxy for price targets).

This study investigates a third potential contributor to low quality price targets; namely, the possibility that some sell-side analysts use inefficient heuristics to set their price targets. Even analysts adept at formulating accurate earnings forecasts may favor the use of simple valuation heuristics rather than more rigorous and proven techniques.[2] Using a broad sample of

[2] The popularity of simple valuation heuristics can be traced to their ease of implementation and to the absence of unambiguous feedback about their actual success or failure in use. Feedback can be ambiguous because, under certain circumstances, the investment signals generated by a simple valuation heuristic can be consistent with those derived from more rigorous valuation techniques (e.g., Easton 2004; Penman 2005). *Value Line*, for example, says

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 technique yields higher quality price targets as measured by realized investment returns over a 12-month horizon. Our tests control for possible differences in earnings forecast accuracy (including an optimistic bias) and its association with inferred valuation model use.

Three research questions thus anchor the study. First, do analysts' price target opinions predict future stock returns? We document the 12-month holding period abnormal returns realized by portfolios constructed from analysts' price target opinions and find that realized returns are greater for more favored stocks but the relation is not strictly monotonic. Second, does *inferred* valuation model use moderate the ability of analysts' price targets to predict future returns? The valuation models considered here incorporate analysts' earnings forecasts and yet differ in simplicity and rigor. Reliance on a less rigorous valuation model may diminish the investment advantage associated with an analyst's more accurate earnings forecast but it may also mitigate the disadvantage of less accurate forecasts. Our final research question is motivated by the need to isolate any incremental effects of *inferred* valuation model use on realized returns from those associated with differences in earnings forecast accuracy and recommendation opinions. Loh and Mian (2006) and Ertimur et al. (2007) both find that analysts who issue more accurate EPS forecasts also provide more profitable Buy/Sell recommendations. Our third research question thus sheds light on the relative influence of valuation model use on price target investment performance.

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that the price targets produced by its analysts are based on the analyst's projections for earnings multiplied by an estimated price/earnings ratio (http://valueline.com/ed_vlpage.html and Brav, Lehavy, and Michaely 2005). This simple valuation heuristic may be efficient in some circumstances and inefficient in others.

Our key finding is that substantial improvements in price target investment performance occur when analysts appear to use a rigorous valuation technique rather than an heuristic. This improvement in realized returns is most pronounced among analysts who are also adept at formulating accurate earnings forecasts, a key input to the valuation models we consider. Our results are robust to a battery of sensitivity tests. 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.

Our study contributes to several streams of ongoing research. First, the study adds to a growing literature on the role of analysts' price targets as information signals (Brav and Lehavy 2003; Asquith et al. 2005). We show that analyst price targets predict future returns, and that this effect is incremental to the returns predictability of Buy/Sell recommendations. Second, the paper extends Bradshaw's (2002, 2004) research on valuation model choice and analysts' investment opinions. Third, the study sheds light on the relative importance of valuation model use to the profitability of analysts' price targets. Finally, the study makes an important methodological contribution by developing an approach to inferring analysts' valuation model use in large samples. Despite the inherent limitations of inferring analysts' unobservable valuation models from imperfect signals, which we discuss at the end of Section 3, we believe our approach has broad applicability for generating new insights about how analysts' earnings forecasts, price targets, and recommendations are intertwined.

We present the remainder of the paper in five 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 sample firms and analysts. The results are presented in section 4. We discuss supplemental analyses in section 5. Concluding remarks are provided in section 6.

2. Prior research

Sell-side equity analysts collect, evaluate, and disseminate information about future financial and investment performance of the firms they cover. Many 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 investment recommendation. Descriptions of the equity research process (e.g., Copeland, Koller, Murrin 2000; English 2001; Penman 2010) indicate that the quality of an analyst's Buy/Sell recommendation depends on how well each of three distinct 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 adept at forecasting earnings and other firm fundamentals may use those superior forecasts as inputs to a flawed valuation technique thereby generating inferior price targets and recommendations.

This section summarizes earlier research on the prevalence and informativeness of analysts' price target opinions and on whether earnings forecast accuracy and valuation model choice influence price target investment performance.

Analysts' price targets

Asquith et al. (2005) report 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] Among this group of top-rated analysts, 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).

Price target revisions are accompanied by a mean five-day abnormal stock return of -3.9 percent around downward revision announcements and +3.2 percent for upward revisions (Brav and Lehavy 2003). The stock return associated with price target revisions is comparable in magnitude to that for changes in Buy/Sell recommendations (Asquith et al. 2005).[4] Price target revisions are more frequent than recommendation changes but analysts often issue revised price targets and Buy/Sell recommendations simultaneously. Both studies confirm that changes in summary earnings forecasts, stock recommendations, and price targets each provide independent value-relevant information to the capital market.[5]

Investor reaction to analysts' price target revisions is justified only if price targets convey incremental information useful for predicting future stock prices. But some have argued that

[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 percent for the current fiscal year and 95 percent for at least one subsequent year. Only 23 percent 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] Brav and Lehavy's (2003) findings may overstate investor reaction to price target revisions. Altinkilic and Hansen (2009) find that analysts Buy/Sell recommendation revisions often piggyback on other recent corporate news and that recommendation revisions are associated with economically insignificant mean share price reactions after controlling for this other news. The same may be true for price target revisions. Our interest is in the ability of price targets to predict future stock returns rather than the information content of price target revision announcements.

[5] 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 stock returns that accompany the issuance of sell-side research reports. The stronger the justifications provided in the report, the stronger the market's reaction to the report. Recent evidence derived from intra-day stock returns (Altinkilic and Hansen 2009; Altinkilic, Balashov, and Hansen 2009) raises new questions about whether analysts' earnings forecasts and stock recommendations are an important source of incremental information for investment purposes or just piggyback on other recent news.

published price targets may at times serve a quite different purpose. Analysts have incentives to compromise their objectivity and optimistically bias their commentaries, forecasts, price targets, and recommendations (e.g., Lin and McNichols 1998; Michaely and Womack 1999; Dechow, Hutton, and Sloan 2000; Bradshaw, Richardson, and Sloan 2003; Lin, McNichols, and O'Brien 2005). Asquith et al. (2005, 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 performance 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). Stocks that attain the price targets of these top-rated analysts usually overshoot by an average of 37 percent during the ensuing 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 attainability of 95,852 price targets for U.S. firms issued in 1997-2002. Only 45 percent of these price targets are attained in the ensuing year.

Price target attainability is an incomplete performance measure 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 the next 12 months to attain an $11 price target than 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 performance measure.

Our first research goal is then to document the investment returns realized by portfolios built from analysts' price targets. This is the first study to provide large sample evidence on whether analysts' price targets predict future stock returns. If price target opinions do indeed predict future market prices, then the *ex ante* return implied by the price target when first published (e.g., 10 percent for an $11 price target assigned to a $10 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 worth of a stock. Of course, a positive association between implied returns and realized returns does not preclude the possibility that price targets are sometimes influenced by other considerations as well.

Analysts' valuation model choice

Stock valuation methodologies fall into one of two broad categories: so-called *fundamental valuation methods* such as the discounted cash flow (DCF) approach that combine projected cash flows or earnings 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. As Penman (2010, 74) notes: "In valuation, as with most technologies, there is always a tradeoff between simple approaches that ignore some pertinent features and more elaborate techniques that accommodate complexities".

Valuation multiples are heuristics derived from informal methods and experience. They are simple to apply and communicate but use limited information about the firm, its factor and product markets, future prospects, or industry competition. Damodaran (2005, 754) has characterized analysts' use of relative valuation multiples as "a story telling experience; analysts with better and more believable stories are given credit for better valuations". Fundamental valuation methods, on the other hand, are theoretically sound but challenging to implement and communicate. They require analysts to identify all the relevant information and then to extract from that information the applicable implications for valuing the firm and its securities. Despite important theoretical and practical differences in the two valuation methodologies, they can lead to identical price targets under certain circumstances.

What valuation methodologies do sell-side analysts use when formulating price targets? Two strands of research are pertinent. One strand provides evidence on *self-reported* valuation model use. Demirakos, Strong, and Walker (2004), for example, report that only half of the 104 comprehensive research reports in their sample of London Stock Exchange listed companies mention DCF valuation models or 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: 99 percent of the reports examined by Asquith et al. (2005) mention an earnings multiple (e.g., price-to-earnings) but only 13 percent mention the use of DCF or its variations. 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 present value [DCF] 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' stated price targets (or recommendations) and researcher-constructed valuation estimates. A high observed correlation means that analysts' price target opinions behave "as if" they were formed according to the particular valuation methodology under consideration. Bradshaw (2002) compares the price targets sell-side analysts disclosed in a hand-collected sample of 67 research reports on U.S. firms with *pseudo*-price targets constructed from PEG ratios and from industry-adjusted P/E multiples that incorporate analysts' one-year and two-year-ahead earnings forecasts.[6] PEG-based *pseudo*-price targets are more highly correlated with analysts' actual price targets than are *pseudo*-price targets constructed from industry P/E multiples. Bradshaw (2002) does not examine the explanatory power of *pseudo*-price targets constructed from DCF or residual income valuation models.

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. 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

[6] The PEG ratio is a firm's price-to-forward-earnings (P/E) ratio divided by its forecasted long-term earnings growth (G) rate. PEG ratio advocates claim that a value greater than one constitutes a Buy signal. Numerous articles in the financial press describe the pervasive use of the PEG ratio as a stock investment tool, but Easton (2004) is the first to provide a formal derivation of PEG by imposing simplifying assumptions on fundamental valuation theory.

favored by the PEG model. Consensus recommendations are not well explained by consensus *pseudo*-price targets constructed from either DCF valuation model. 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 fundamental 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 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.

As our second research goal, 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. In contrast to Bradshaw (2004), we focus on analysts' price target opinions because they are more granular, more verifiable, and more comparable across analysts than are Buy/Sell recommendations and because large sample price target data files are now available in electronic form. 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 and thus provide an inconclusive basis for

inferring valuation model use. Our tests also control for potential differences in analysts' EPS forecast accuracy because earnings forecasts are inputs to the valuation models we consider.

Analysts' earnings forecast accuracy

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.[7] Loh and Mian (2006) and Ertimur et al. (2007) both find that analysts who issue more accurate EPS forecasts also provide more profitable Buy/Sell 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, earnings forecast accuracy and future stock returns. At the extreme, concocted price targets would presumably exhibit little or no predictive ability for future stock returns.

As our final research goal, we extend 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. Forecasting and valuation are two distinct tasks analysts perform and we conjecture that the potential benefits of

[7] Prior research documents that during the 1980's, analysts' forecasts were, on average, optimistic (see, e.g., O'Brien 1988; Butler and Lang 1991). However, firms' ability to meet or beat analysts' earnings forecast benchmarks in recent periods is more consistent with forecast pessimism (see, e.g., DeGeorge, Patel, and Zeckhauser 1999; Bartov, Givoly, and Hayn 2002; Kasznik and McNichols 2002; Matsumoto 2002; Richardson, Teoh, and Wysocki 2004; and Burgstahler and Eames 2006). Sustained differences exist over time in the EPS forecast accuracy of individual analysts (Stickel 1992; Sinha, Brown, and Das 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).

superior EPS forecasts for price target quality can be lost if those forecasts are used as inputs to a flawed stock valuation model. Our tests rely on concurrent EPS forecast accuracy (as in Loh and Mian 2006) and control for concurrent Buy/Sell recommendations.

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.

Potentially "stale" price targets that are outstanding for more than one year are discarded because most price targets are issued with a 12-month horizon. We require the analyst to update at least one earnings forecast in the subsequent 12 months, which reduces the likelihood that our price targets are from analysts that stop coverage of the firm. We also require analysts' one-year EPS forecasts from I/B/E/S to be "current," meaning newly issued in the fourth month after the company's fiscal year-end or issued previously but confirmed by I/B/E/S—and thus reiterated by the analyst—in that same month or later. This filter reduces the likelihood that stale EPS forecasts contaminate our sample. These data restrictions collectively yield a preliminary price

target sample of 64,281 analyst/firm/year 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. Consistent with Bradshaw and Brown (2006) and Frankel and Lee (1998), we delete firms with share prices below $1 so that our results are not influenced by stocks with low liquidity and thus high trading costs. The inclusion of stocks with extremely low share prices may have a disproportionate effect on our results because such stocks are often thinly traded. Excluding these stocks from our sample means that our results may not generalize to the population of low-priced, illiquid stocks. 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. This step is intended to mitigate the influence of errors (if any) in the First Call database.

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 (as 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 and actual earnings are subsequently reported; (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 values of *AFE* for each firm-year.[8] Requirement 3 mitigates the influence

[8] We note that the requirement that actual earnings be announced may impose a survivorship bias. However, this requirement is typical in studies that measure analysts' earnings forecast accuracy. 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

of I/B/E/S data errors on our accuracy rankings. Requirement 4 ensures that each firm-year combination is represented in each EPS forecast accuracy quintile (Loh and Mian 2006). These restrictions further reduce the 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 of price targets and Buy/Sell recommendations among analysts who supply earnings forecasts to I/B/E/S each year. The I/B/E/S EPS Forecasts sample is comprised of 136,790 analyst-firm-year observations that pass the forecast accuracy (*AFE*) quintile filters described earlier. The Recommendations sample (n = 93,594) is the subset of I/B/E/S EPS Forecasts that also have a Buy/Sell stock recommendation outstanding in the fourth month after the firm's fiscal year-end. Price targets are not required for the two comparison samples. Panel A also reports the average *ex ante* (implied) return associated with analysts' price targets, 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 price target submission date. Values of *PT/P* greater than one presumably convey the analyst's belief that the stock is an attractive investment opportunity whereas values less than one indicate an unattractive stock.

There are several messages in the Panel A data. 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

avoid rounding errors common to the split adjustment process and to ensure that all variables are stated on the same basis.

1997 to 50 percent in 2002 and 2003.[9] 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.

[Insert Table 1]

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. This is consistent with the mean recommendation of 2.12 which represents a "Buy" signal. 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 declines to 1.26 by 2003. 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 one). 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. The increased frequency of sell recommendations (9.8 percent) and pessimistic price targets (12.7 percent) in 2003 compared to earlier years may be due to changes in the regulations governing stock research reports (Barber, Lehavy, McNichols, and Trueman 2006).

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 one—to "most favored" stocks comprising the top quartile of observations where *PT/P* is greater than one. This sorting process preserves

[9] Price target availability in our broad sample is below the 73 percent reported by Asquith et al. (2005) for stock research reports authored by *Institutional Investor* "All American" analysts during 1997 to 1999. Apparently, the inclusion of explicit price targets in published research reports is one of the hallmarks of "All American" analysts.

the natural distinction between presumably overvalued (*PT/P* < 1) and undervalued (*PT/P* > 1) stocks, and is responsive to the obvious asymmetry in the distribution of observed *PT/P* values.

The central message in panel B is that analysts' Buy/Sell recommendations and price target opinions typically convey a consistent viewpoint regarding the investment value of a given stock; i.e., stocks assigned the highest recommendation also tend to be those most undervalued according to their implied investment return (*PT/P*). A surprising second message is that analysts' price targets and recommendations sometimes provide discordant investment signals. For example, one out of every five of the 181 "Strong Sell" stocks in our sample is also deemed by analysts to be undervalued (*PT/P* > 1) rather than overvalued, and 11 percent of the "Sell" recommended stocks are in the "most favored" *PT/P* group with the highest implied investment return. Discordant investment signals are also present among "Buy" and "Strong Buy" stocks. This pattern echoes earlier findings drawn from limited samples of price targets and recommendations (e.g., Asquith et al. 2005; Bradshaw 2002) and suggest that analysts' 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.

There are several possible explanations for discordant price targets and recommendations. Even if analysts rely exclusively on price target profitability to determine their recommendations, the panel B data may not cluster tightly along the concordant diagonal if individual brokerage houses (or analysts) differ in the *PT/P* cutoffs used for each recommendation category. Differences in recommendation cutoffs are, however, unlikely to fully explain the directional mismatches evident in the Panel B data.

Discordant investment signals will arise naturally if recommendations are intended to convey the analyst's relative (not absolute) investment opinion. An analyst covering 10

insurance stocks, all of which seem correctly valued from a price target perspective (*PT/P* ≈ 1 for each firm) may still feel compelled to assign a "Strong Buy" to the best one in the group. As an illustration, Allstate Corporation received a "Strong Buy" rating when the CBC Oppenheimer analyst's price target predicted appreciation of only 4.5 percent which places this stock in the "least favored" *PT/P* group in Table 1. Despite the small profit opportunity, the analyst still viewed Allstate as the best stock in the property-casualty personal insurance group of four firms.

Discordant observations can also arise from production errors made by data providers. To investigate the possibility of I/B/E/S (recommendation) and First Call (price target) data errors, we randomly selected 40 discordant observations and traced them to published research reports. We found one price target data coding error but no recommendation coding errors.[10] Published research reports that include a price target also contain the analyst's stock recommendation. This means that the existence of discordant investment signals cannot be traced to the possibility that one or the other signal is somehow stale (see Section 5 for more discussion of signal timeliness). Of course, the possibility of data production errors by analysts or brokerage houses remains.

The discordant signals in our sample tend to be concentrated among analysts that follow a small number of firms. Twenty percent of the discordant "Strong Buy" recommendations involve analysts that cover no other firm that year, and the median number of firms covered by such analysts is three. Analysts with discordant "Strong Buy" recommendation/price target pairs make significantly more "Strong Buy" recommendations than do concordant analysts (50 percent versus 35 percent; chi-square statistic = 205.3, p-value<0.01). The price targets assigned by discordant analysts to their other "Strong Buy" stocks also are less optimistic, on average, than

[10] I/B/E/S assigns a numerical value to the qualitative Buy/Sell opinions analysts submit; e.g., an I/B/E/S rating of 1 denotes a "Strong Buy" recommendation whereas a rating of 5 denotes a "Strong Sell". Brokerage houses and research firms differ in the labels used for these opinion designations, and some employ fewer than five qualitative categories. Our recommendation coding error test found no instances in which the I/B/E/S numerical rating was directionally inconsistent with the analyst's qualitative opinion.

are those assigned by concordant analysts (mean *PT/P* of 1.36 versus 1.42, *t*-statistic = 3.44, *p*-value < 0.01).

Although discordant price target/recommendation pairs occur in large samples such as ours, their precise origin remains indeterminate. Most importantly, discordant observations are comparatively rare and our results are robust to the exclusion of these observations from the sample.

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.[11] The PEG ratio is selected as our valuation heuristic because of its reliance on analysts' EPS forecasts, its apparent popularity as a basis for stock recommendations (Easton 2004), and its demonstrated superiority for predicting analysts' actual price targets when compared to industry price-earnings multiples (Bradshaw 2002).[12,13] 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

[11] 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 et al. 2000; Penman 2007). Implementation differences across analysts can induce differences in price target quality even when the same DCF model is used.

[12] As Easton (2004) points out, the PEG ratio heuristic is not derived formally from fundamental valuation theory but it can be shown, under certain restrictive assumptions, to be inversely related to a stock's expected rate of return. Trombley (2008) demonstrates that PEG ratios can differ markedly from one even though a stock is correctly valued by market participants.

[13] Liu, Nissim, and Thomas (2002) provide large-sample evidence on the ability of PEG and RIM *pseudo*-price targets to explain actual stock prices over the period 1982-1999. They conclude that PEG outperforms RIM in this particular context, although their implementations of the two valuation approaches differ from those used here. They do not provide evidence on the ability of PEG and RIM *pseudo*-price targets to explain analysts' price targets or predict future stock returns.

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 $\left(EPS_{t+\tau} - r * BVPS_{t+\tau-1}\right)$, *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 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 zero or greater than one). 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 estimate allows *RI* to fade toward zero over time as a result of possible competitive pressures within the industry. We derive an empirical fade rate (ω) for each Fama and French (1997) industry and sample year using all firms with the requisite data

available on Compustat (see Bradshaw 2004 for details). 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:

$$E_t[TV_{t+5}] = \frac{\omega}{1+r-\omega} E_t[RI_{t+5}] \quad (2)$$

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

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

$$V_{PEG} = E_t\left[EPS_{t+2}\right] \times LTG \times 100 \quad (3)$$

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. 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 percent, or where the *pseudo*-price target is extreme.

The ability of RIM and PEG *pseudo*-price targets to explain cross-sectional variation in analysts' actual price targets is described in panel A of Table 2. The panel 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 R^2 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.

[Insert Table 2]

Panel A of Table 2 reports summary statistics describing inferred valuation model use as measured, for a given analyst-firm-year, by $\left(|\varepsilon_{RIM}|/|\varepsilon_{PEG}|\right)$ 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. *VMR* ratio values less than one favor use of RIM by the analyst whereas values greater than one favor use of the PEG heuristic. If RIM and PEG *pseudo*-price targets are equidistant from the actual price target, the *VMR* ratio value will be one and neither approach dominates the other as a description of the price target formation process. 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 and thus provide an inclusive basis for inferring valuation model use.

Despite its intuitive appeal, our approach to inferring valuation model use has several limitations. One is that our implementation of the RIM and PEG valuation models may not accurately capture how the analysts comprising our sample form their price targets. Research-

induced implementation differences may cause the resulting *pseudo*-price targets to deviate from analysts' actual RIM or PEG price targets and this may contribute to error in classifying analysts' valuation approaches. This possibility may be more acute for RIM *pseudo*-price targets than for PEG *pseudo*-price targets given the relative simplicity of the PEG approach. However, our reliance on *VMR* and its large-sample regression estimates of valuation model fit mitigate any systematic bias attributable to implementation differences. Our findings are robust to a battery of RIM model implementation sensitivity tests described later in the paper.

A second limitation is that our *pseudo*-price targets are derived from analysts' published earnings forecasts which may differ from the private forecasts used as inputs to their valuation models. This possibility may also contribute to error in classifying analysts' valuation model approaches. However, our RIM and PEG *pseudo*-price targets are derived from a common set of analysts' EPS forecasts and our tests control for cross-sectional differences in contemporaneous earnings forecast accuracy. The limited availability of analysts' two-year-ahead EPS forecasts and long-term EPS growth estimates—required for *both* RIM and PEG pseudo-price targets, and thus *VMR*—reduces the pseudo-price target sample to 21,202 analyst/firm/year observations.

A third limitation is that our approach ignores the endogeneity of analysts' valuation model use. For example, analysts that rely on a PEG approach may do so because discount rates are required for the implementation of RIM but not for PEG. It is also possible that analysts who use RIM perceive risk (i.e. discount rate) differently than analysts who use PEG valuation. Analysts who in fact use PEG valuation may do so to avoid the problem of estimating a discount rate. Finally, *VMR* only indicates whether analysts' price targets behave "as if" the RIM or PEG approach is being used. It is entirely possible that some analysts employ a third (unidentified)

approach that coincidentally results in a price target closely approximating our RIM (or PEG) *pseudo*-price target.

As shown in panel A of Table 2, analysts' actual price targets do not exhibit a consistent pattern of deviation from RIM and PEG *pseudo*-price targets across the sample period. They initially favor RIM use (median *VMR* of 0.76 in 1997), then increasingly favor PEG use (median *VMR* of 1.16 in 2000), before trending back toward RIM use (median *VMR* of 0.97 in 2003). It is noteworthy that RIM *pseudo*-price targets exhibit little explanatory power in both 2000 and 2001 (adjusted R^2 of 0.14 and 0.36, respectively), the two years in which analysts' price targets most strongly favor PEG use. Panel B of Table 2 reports summary *VMR* statistics by price target profitability (*PT/P*) portfolio and Buy/Sell recommendation category. Apparent RIM use is prevalent among stocks in the top ("most favored") *PT/P* profitability portfolio and those with a "Strong Buy" recommendation. PEG use is prevalent among "least favored" and "disfavored" *PT/P* stocks as well as those with a "Hold" rating. Implied valuation model use thus varies over time (panel A) and across *PT/P* profitability portfolios and recommendation categories (panel B).

4. Results

Price target investment performance

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. This approach

controls for differences in market-wide share price movements over the investment holding period. We then compute the average *BHAR* for each price target implied return (*PT/P*) portfolio. 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 *PT/P* portfolios.

Table 3 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 one, 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 percent compared to the reliably negative -1.42 percent *BHAR* earned by "least favored" Portfolio 2 stocks. The *BHAR* for "disfavored" stocks is indistinguishable from zero even though share prices are predicted by analysts to decline.

[Insert Table 3]

Investment performance and valuation model use

Table 3 also provides evidence on whether valuation model use influences the quality of analysts' price target opinions. To investigate this question, we form portfolios grouped by price target implied return (*PT/P*) and inferred valuation model use (*VMR*). The six *VMR* portfolios are constructed by sorting observations where *VMR* is less (greater) than one into terciles each year. This approach preserves the natural distinction between *VMR* values that favor RIM versus PEG use and controls for the time-series variation in average *VMR* evident in Table 2.

Three 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* Portfolio 1). For example, *VMR* Portfolio 1 stocks belonging to the "disfavored" *PT/P* portfolio earn a 12-month abnormal return of -4.67 percent compared to the reliably positive 10.46 percent

BHAR earned by stocks in the "most favored" *PT/P* portfolio. A similar (but non-monotonic) pattern of returns is evident for the other two *VMR* portfolios that imply RIM use. Second, *BHA*R does not increase across price target portfolios when *VMR* implies use of the PEG valuation approach (*VMR* Portfolio 6). The *BHAR* for "disfavored" stocks in this *VMR* portfolio is 0.80 percent and statistically indistinguishable from zero whereas the "most favored" stocks earn a reliably negative -4.64 percent return. Finally, *VMR* Portfolio 1 (RIM use) stocks outperform *VMR* Portfolio 6 (PEG use) stocks in every price target profitability group, although the performance differential is statistically significant only for "most favored" *PT/P* stocks (*BHAR* of -15.10 percent).

Recall that the explanatory power of RIM and PEG *pseudo*-price targets for actual price targets varies over time (panel A of Table 2), and is especially low in 2000 and 2001. By contrast, the investment performance of *VMR* portfolios is remarkably stable across time. Untabulated tests confirm no detectable change—deterioration or improvement—occurs in *BHAR* investment performance of *VMR* Portfolio 1 (RIM use) stocks during this two-year period. The same holds true for the other *VMR* portfolios, with one exception: there is a statistically significant ($p < 0.01$) decline in *BHAR* investment performance for *VMR* Portfolio 6 (PEG use) stocks during 2000 and 2001. Moreover, the performance decline is evident in each of the Table 3 price target profitability (*PT/P*) categories.

Collectively, the results in Table 3 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' 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? To investigate this question, we adopt the approach of Loh and Mian (2006) and sort all 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:

$$AFE_{ijy} = \left| Actual_{ijy} - Forecast_{ijy} \right| \quad (5)$$

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 by subtracting 0.25 from the assigned rank and dividing the result by the maximum firm-year rank. Subtracting 0.25 from the assigned rank serves to equalize the observations allocated to extreme quintiles (Loh and Mian 2006). We then sort analysts for a given firm and year into quintiles based on the percentile score.

This approach to measuring *relative* EPS forecast accuracy has several desirable properties when compared to the cross-sectional price deflated absolute forecast error measure

common to the literature. In particular, the approach facilitates accuracy comparisons by controlling for the inherent difficulty of the forecasting task, which can vary across companies and over time for a given company. Analysts are assigned to different accuracy quintiles based on their demonstrated ability to forecast EPS for the same firm and year. 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.[14]

Table 4 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 targets to First Call, the mean scaled *AFE* is 0.024 (i.e., 2.4 percent 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.

[Insert Table 4]

Between-sample *t*-tests in Table 4 document the superior earnings forecast accuracy of analysts who submit price targets to First Call when compared to the larger population of I/B/E/S analysts who provide earnings forecasts and Buy/Sell recommendations (but perhaps no price

[14] Following Loh and Mian (2006), analysts are assigned to EPS forecast accuracy quintiles based on current year forecast performance rather than prior year performance. This feature strengthens the power of our tests by eliminating noise in the accuracy quintiles but the simulated trading strategy is not implementable and thus the investment performance results in Tables 5 and 6 do not reflect returns actually available to investors. As supplemental analysis, we report results obtained when accuracy quintiles are based on prior year forecast performance. This approach adds noise to the accuracy quintiles but renders our stock return findings that control for differences in analyst forecast accuracy more readily interpretable as the investment performance associated with an implementable trading strategy.

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 covered firms are represented in both analyst samples.

Evidence on whether *inferred* valuation model use varies across earnings forecast accuracy (*AFE*) quintiles is provided in Table 5. Analyst-firm-year observations within each *AFE* quintile are sorted by inferred valuation model use (*VMR* portfolio) each year. 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* Portfolio 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* Portfolio 6.

[Insert Table 5]

The data in panel A of Table 5 refute these predictions. Earnings forecast accuracy is instead uncorrelated with valuation model use. *AFE* quintiles are distributed almost uniformly within each *VMR* portfolio in that each cell of the table contains about 16 percent of the corresponding *AFE* observations. This means that valuation model use is independent of earnings forecast accuracy. Analysts with the most accurate EPS forecasts are neither more nor less likely to use a RIM valuation approach than are analysts with the least accurate earnings forecasts. One implication of this result is that the skills and techniques required for forecasting earnings (and other firm fundamentals) may be quite different from those needed to infer the implications of future earnings for firm value.[15] We examine factors affecting valuation model use in supplemental analysis.

[15] An alternative explanation for this result is that our forecast accuracy quintile assignments may exaggerate small accuracy differences because analysts covering the same firm in a given quarter are forced into each of the five *AFE*

Earnings forecast accuracy and price target profitability

Table 5 panel B reports average *BHAR* by earnings forecast accuracy (*AFE*) quintile and price target (*PT/P*) portfolio, both formed as previously described. If forecast accuracy differences affect 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.

Consider, for example, the investment performance of "most favored" stocks (*PT/P* portfolio 5). As shown in panel B of Table 5, stocks in this portfolio earn, on average, a reliably positive abnormal return of 8.07 percent 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 percent 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 almost every *PT/P* portfolio based on the Q1-Q5 hedged returns.

A second message in the data is that price targets are informative for investment purposes only when contemporaneous 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 percent compared to an average return of -2.17 percent 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

quintiles. However, as the multivariate results in Table 6 indicate, *AFE* quintiles are predictive of future stock returns. This means that the accuracy differences across quintiles are economically meaningful and casts doubt on the possibility that our methodology is responsible for the apparent independence evident in Table 5.

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 percent compared to the positive 8.02 percent return for disfavored stocks.

These results could simply reflect analysts' "lucky guesses" with respect to both price targets and contemporaneous earnings forecasts, although supplemental tests confirm this finding when historical EPS forecast accuracy is instead used. We suspect that price target investment performance derives in part from analysts' valuation model choices. To investigate this possibility, we next provide evidence on whether and how *inferred* valuation model use influences price target profitability after controlling for earnings forecast accuracy.

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 (*PT/P*), inferred valuation model use (*VMR*), and earnings forecast accuracy (*AFE*). 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 scaled to range between zero and one, and capture information about the ordinal ranking of the data.[16] 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*)

[16] For example, *REC_rank* equals zero if the analyst's stock recommendation is a "Strong Sell" and one when it is a "Strong Buy". Similarly, *PT/P_rank* equals one when the price target opinion denotes as a "most favored" stock, *AFE_rank* equals one for the top quintile ("most accurate") EPS forecasts, and *VMR_rank* equals one when RIM is the inferred valuation approach.

is equal to one for a portfolio characterized by high earnings forecast accuracy and inferred 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.[17] 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 reliably positive 16.68 percent abnormal return over the ensuing 12 months.[18] 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 -4.44 percent 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.

[Insert Table 6]

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"

[17] The regression model requires a Buy/Sell recommendation for each analyst-firm-year observation and this reduces the sample to 18,804. Observations with studentized residuals greater than three 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 and time-series clustering of observations (Huber 1967; White 1980).

[18] 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/P* coefficient estimate of -15.00 percent in panel A is correctly interpreted (when combined with the +8.12 percent intercept) as the return to a portfolio characterized by "most favored" price target profitability (*PT/P_rank* = 1) but "least accurate" earnings forecasts (*AFE_rank* = 0) and inferred use of the PEG valuation approach (*VMR_rank* = 0). This portfolio earns a return of -6.88 percent, or (-15.00 percent + 8.12 percent). Including *REC_rank* in the contrast tests in panel B alters the level of the benchmark portfolio return but does not affect the level or significance of incremental returns for changes in portfolio composition.

earnings forecasts, and RIM valuation model use that earns a return of 16.68 percent. *BHAR* falls by 10.66 percent when the portfolio is tilted to PEG use; by 16.30 percent when the portfolio is tilted to the least accurate earnings forecasts; and by 23.57 percent when both valuation model use and earnings forecast accuracy are changed. This sharp deterioration in realized returns confirms the incremental influence of RIM 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 (-6.89 percent = 16.68 percent - 23.57 percent) when analysts in the bottom EPS forecast accuracy quintile behave as if they 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 -4.44 percent in panel B for disfavored *PT/P* stocks with the "most accurate" earnings forecasts and RIM valuation model use. *BHAR* increases by 5.58 percent when the portfolio is tilted to PEG use; by 10.32 percent when the portfolio involves analysts with the "least accurate" earnings forecasts; and by 12.55 percent when valuation model use and earnings forecast accuracy are both changed. Investors can earn a positive 8.11 percent *BHAR* by purchasing (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 34.63 percent while the *BHAR* for "disfavored" *PT/P* stocks is -9.32 percent.[19] 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 12.05 percent when analysts' price targets imply PEG use, and by 17.22 percent 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 15.79 percent but PEG model use has no statistically discernable impact on performance.

Collectively, our results document that substantial improvements in price target quality occur when analysts appear to be using a fundamental 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. In supplemental tests described next, we provide evidence on whether these results are robust to the use of historical, rather than concurrent, EPS forecast accuracy. We also provide evidence on factors associated with valuation model use, whether our findings are sensitive to earnings forecast or price target timeliness, and on the relative value of price targets versus Buy/Sell recommendations for investment purposes.

5. Supplemental analysis

Historical forecast accuracy

[19] The benchmark *BHAR*, 34.63 percent in the case of the portfolio of "most favored" *PT/P* stocks, omits any incremental return associated with *REC_rank* (see footnote 18). Inclusion of this omitted return decreases the benchmark *BHAR* for "most favored" stocks to 16.97 percent. There is little cross-sectional variation in analysts' Buy/Sell recommendations for "most favored" stocks, and this may contribute to the large negative incremental return associated with *REC_rank*.

Our primary findings make use of Loh and Mian's (2006) earnings forecast accuracy metric which means that EPS forecast accuracy is measured concurrently with the stock return holding period. This *ex post* accuracy measure has several research design advantages that are important to our study but its use also means that the differential stock returns documented in Tables 5 and 6 do not reflect investment profits arising from an implementable trading strategy. On the other hand, prior studies find evidence of persistent differences in EPS forecast accuracy across analysts (Stickel 1992; Sinha et al. 1997), which implies that our investment results are likely to be qualitatively robust to the use of *ex ante* (historical) forecast accuracy.

To investigate this question, we re-estimate the Table 6 regression using prior year EPS forecast accuracy where *AFE* portfolios are again formed using Loh and Mian's (2006) method and lagged *AFE*. Data requirements reduce the number of analyst-firm-year observations available for estimation purposes by roughly 40 percent. As expected, the results (not tabulated) from using historical EPS forecast accuracy are qualitatively similar to those reported in panel C of Table 6. In particular, among most favored stocks (top *PT/P* group), RIM-based price target opinions are statistically more profitable for investment purposes than are PEG-based price targets. As in Table 6, this return differential is reduced but not eliminated when EPS forecast accuracy declines. The RIM versus PEG stock returns differentials for the other *PT/P* categories are, for the most part, statistically insignificant but directionally consistent with those in Table 6.

Correlates of valuation model use

Although a comprehensive analysis of the determinants of valuation model use is beyond the scope of this study, we offer preliminary evidence on this question by investigating the association between valuation model use and characteristics of the analyst, brokerage house, and covered firm. We conjecture that a given analyst will use the same RIM or PEG approach for all

covered firms, and that analysts employed at the same brokerage house or research firm will tend to use similar valuation methodologies.

Three characteristics of each analysts are considered: prior year forecast accuracy (lagged *AFE*); prior year inferred valuation model use (lagged *VMR*); and *Expertise*, defined as the number of previous years in which the analyst has issued EPS forecasts. All three characteristics are measured at the analyst-firm level. Brokerage house characteristics include *BSize*, defined as the number of I/B/E/S analysts employed that year by the brokerage or research firm, and *Conflict* which captures information about possible investment banking-related conflicts of interest that may influence analysts' opinions. As in Ertimur et al. (2007), our *Conflict* measure is the Carter-Manaster investment banking reputation rankings (Carter and Manaster 1990; Carter, Dark, and Singh 1998) as updated by Loughran and Ritter (2004). Analysts employed by brokerage firms with significant investment banking business are regarded for test purposes as potentially conflicted. Covered firm characteristics include: *FSize*, measured as the beginning-of-year market value of equity; the beginning-of-year book-to-market (*BM*) ratio; and *HighTech*, an indicator variable denoting firms in the high technology industries (SIC codes between 7370 and 7379). With the exception of *HighTech* and *Conflict*, all variables are sorted into quintiles and then scaled to range between zero and one. Three *Conflict* categories are defined: a value of one is assigned if the brokerage firm has the top investment banking reputational rank; lower reputational ranks are assigned a value of 0.5; and zero is assigned to brokerage and research firms that do not have a Carter-Manaster reputation ranking. *HighTech* remains an industry indicator variable.

The results (not tabulated) of regressing analyst, brokerage, and firm characteristics on *VMR* reveal that *inferred* RIM valuation model use exhibits a statistically positive association

with prior year RIM use (lagged *VMR*, $t = 20.07$, $p \leq 0.01$) and a reliably negative association with brokerage firm size (*BSize*, $t = -2.26$, $p \leq 0.05$). The regression coefficients associated with the other analyst/brokerage characteristics are statistically indistinguishable from zero. Two covered firm characteristics exhibit reliably negative associations with RIM use: *FSize* ($t = -4.89$, $p \leq 0.01$) and book-to-market ratio (*BM*, $t = -4.67$, $p \leq 0.01$). The *HighTech* coefficient is positive but not statistically different from zero. Although we are somewhat guarded about drawing inferences from these results given the preliminary nature of the analysis, the data suggest that valuation model use may be a relatively persistent attribute of the analyst/firm pairing. Moreover, RIM use is somewhat more prevalent among analysts employed at small brokerage houses and among analysts who cover small firms or firms with low book-to-market ratios. On the other hand, PEG use is more prevalent among analysts at large brokerage houses and those who cover large firms or firms with high book-to-market ratios.

Valuation model use as an analyst trait

If valuation model use is a relatively persistent trait, the investment performance superiority of price targets associated with inferred RIM model use evident in Table 6 (derived from analyst/firm/year observations) should also be present in portfolios constructed at the analyst level. To investigate this question, we construct a composite *VMR* across years and covered firms for each analyst and then again sort observations where *VMR* is less (greater) than one into terciles. This approach again controls for the possibility that the RIM and PEG valuation approaches yield similar *pseudo*-price targets. The Table 6 results are robust to this substitution and confirm that *BHAR* performance declines when price target portfolios are tilted toward PEG rather than RIM valuation model use by the analyst.

Timely price targets and earnings forecasts

Returning to our primary tests and findings, untabulated results show that the beginning-of-year price targets issued by analysts in the bottom EPS forecast accuracy group (*AFE* Quintile 5) are 15 trading days older on average than those issued by analysts in the top *AFE* group ($p \leq 0.01$). There is no statistical 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 are negatively related to realized returns ($p \leq 0.10$), a result that could be due to their concentration in the low EPS forecast accuracy quintile, but the Table 6 results are qualitatively unchanged when *PT* timeliness is incorporated into the regression model. Prior research has shown that analysts' stale earnings forecasts are less accurate than are timelier forecasts (e.g., Brown, Griffin, Hagerman, and Zmijewski 1987; O'Brien 1998; Brown, Richardson, and Schwager 1987; Lys and Soo 1995). Untabulated results for our sample indicate that analysts in the bottom earnings forecast accuracy group (*AFE* Quintile 5) issue less timely annual EPS forecasts than do those in the top *AFE* quintile. 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 ($p \leq 0.01$). This finding means that forecast timeliness may be partially responsible for differences across *AFE* quintiles in realized returns (*BHAR*). As was the case with stale price targets, stale earnings forecasts are negatively related to realized returns ($p \leq 0.10$) but the Table 6 results are qualitatively unchanged when forecast timeliness is incorporated into the regression model.

Our earnings forecast timeliness measure is derived using initial issuance dates rather than the more timely reiteration dates implicit in the monthly consensus, and thus overstates the

extent to which "old" earnings forecasts, price targets, and recommendations are in fact stale. Apparent differences in the relative timeliness of analysts' recommendations and price targets stem from the use of so-called initial "announcement" dates provided by I/B/E/S and First Call. In aligning recommendations and price targets, we require the analyst's price target announcement date from First Call to fall between the analyst's I/B/E/S recommendation announcement and review dates, where the review date denotes the most recent date the recommendation was confirmed by I/B/E/S as accurate. This process can, for example, align a price target first announced in April 2000 with a "Strong Buy" recommendation first announced in July 1997 because the recommendation is unchanged as of April 2000 and confirmed as accurate. Although the mean difference between recommendation and price target announcement dates in our sample is 173 days (median 79 days), there is no actual difference in the timeliness of these two data items because each Buy/Sell recommendation is reiterated by the analyst in the first published report that contains the price target.[20] Our conclusions about the incremental explanatory power of price targets and recommendations for returns (Table 6) are robust to excluding observations where the difference in announcement dates is greater than 90 days.

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 percent *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

[20] As another example of how a researcher's use of initial "announcement" (issue) dates can lead to false inferences about the data, the mean difference between recommendation and price target announcement dates for discordant investment opinions (i.e., Buy/Sell and *PT/P* mismatches) is 255 days although each recommendations is reiterated with initial publication of the price target. Using announcement dates for research purposes can sometimes result in incorrect inferences about timeliness.

reduction in portfolio performance. This counter-intuitive result is confirmed in untabulated tests where we mimic the analysis in panel C for 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 exhibits a strong and positive association with realized returns in this untabulated analysis. 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 "least accurate" *AFE* quintiles, consistent with the full sample results in panel A, and are insignificant in quintiles 2 and 3.

RIM pseudo-price targets

Bradshaw (2004) finds that investors would earn higher returns over a one-year holding period by relying on RIM *pseudo*-price targets that incorporate analysts' consensus earnings forecasts rather than analysts' consensus Buy/Sell recommendations alone. Our data point to a similar conclusion regarding the superior investment performance of RIM *pseudo*-price targets when compared to analysts' actual price targets.

To investigate this question, scaled quintile measures of RIM and PEG *pseudo*-price target profitability are constructed in the same manner as that used to construct actual price target (*PT/P)* portfolios. The Table 6 regression specification is then augmented to include main and interaction effects associated with these RIM and PEG *pseudo*-price target portfolios. We retain the *PT/P* portfolio variable so that the coefficients associated with the *pseudo*-price targets provide evidence about the incremental *BHAR* investment performance. Untabulated results show that the RIM pseudo-price target portfolio coefficient is reliably positive ($t = 4.25$, $p \leq 0$

.01) whereas the PEG coefficient is not statistically different from zero. The pattern of results for other variables in the *BHAR* regression, including the pseudo-price target interaction terms, is qualitatively identical to that reported in Table 6.[21]

RIM implementation sensitivities

As in Bradshaw (2004), we gauge the sensitivity of our results to various RIM implementation alternatives. In addition to the industry-specific discount rates used in our primary tests, we consider three fixed discount rates (8 percent, 12 percent and 16 percent) and a firm-specific discount rate based on CAPM beta.[22] The RIM forecast horizon for all tabulated results is five years (see equation 1). As alternatives, we consider forecast horizons of two and ten years, where EPS growth beyond year 5 is assumed to either be zero or to adhere to the analyst's long-term growth forecast. We also consider an alternative RIM terminal valuation calculation where residual income in the terminal year is capitalized as a perpetuity rather than adhering to the fade rates assumed in our primary tests. None of the inferences drawn from our primary findings are qualitatively altered by these perturbations to RIM and PEG implementation.

6. 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

[21] Untabulated results also confirm that our primary findings are robust to common 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.

[22] The CAPM discount rate for a particular firm and year is calculated as $r_f + \beta \times E[r_M - r_f]$, where r_f is the risk-free rate proxied by the 30-day treasury bond yield in effect in the most recent calendar month, β is a rolling 60-month estimate of the stock's systematic risk, and the equity risk premium ($E[r_M - r_f]$) is proxied by the historical average equity risk premia for each estimation year as reported by Ibbotson Associates (2010). The historical equity risk premium ranges from 8.25 percent to 8.93 percent during our sample period.

substantial improvements in price target quality occur when analysts appear to be using a 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 departures from RIM valuation model use and inferior earnings forecasts both 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 by our primary findings 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 among 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 factors that determine analysts' valuation model use could also benefit from future research using more refined conjectures and tests than those used here in our preliminary analysis of the question. For example, analysts who are less confident about their medium-term (i.e., three- to five-year ahead) earnings forecasts may favor valuation heuristics such as a forward price/earnings ratio that are insensitive to those forecasts. Analysts employ heuristics presumably because they provide a "fast and frugal" (Gigerenzer, Todd, and the ABC Research Group 1999) mechanism for reducing the complex equity valuation task to a simpler judgmental operation. In general, heuristics are quite useful but sometimes they lead to severe and systematic errors. Future research could build on the results obtained in other judgment and decision-making settings (e.g., Kahneman, Slovic, and Tversky 1982; Hogarth 1990) to investigate more fully analysts' use (and misuse) of valuation heuristics. 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

	I/B/E/S EPS Forecasts			I/B/E/S Buy/Sell Recommendations			First Call Price Targets		
Year	# 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%

Notes:
This panel describes the frequency of price targets (denoted % w/*PT*) and Buy/Sell recommendations (% w/REC) among analysts who supply earnings forecasts to I/B/E/S each year as well as the average *ex ante* (implied) return associated with the 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. 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 except that no published price target is required. 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.

TABLE 1 (Continued)
Panel B: Implied price target profitability (*PT/P*) and buy/sell stock recommendations

	Frequency of Implied Return Category (*PT/P*<1 and then *PT/P* Quartiles) by Recommendation						
Stock Recommendation	Disfavored 1	Least favored 2	3	4	Most favored 5	Frequency of Recommendation	N
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
Mean Implied Return	-15.87	9.53	20.99	33.38	81.59		
Mean *BHAR*	2.46**	-1.08**	-0.32	3.33**	3.15**		
N	3,017	8,056	8,056	8,081	8,031		35,241

Notes:
This panel describes the conditional distribution of implied price target profitability (*PT/P*) by stock recommendation category for 35,241 analyst-firm-year sample observations where a Buy/Sell recommendation is 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. The panel also reports the average implied return (*PT/P* minus 1, expressed as a percentage) and 12-month buy-and-hold abnormal return (*BHAR*) for each *PT/P* group. *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. Significance levels for two-tailed *t*-tests of the null hypothesis that portfolio returns are zero are denoted as *, **, and *** for rejection at the 0.10, 0.05, and 0.01 level, respectively.

TABLE 2
Inferred valuation model use

Panel A: Estimation of inferred valuation model use (*VMR*)

	RIM Valuation			PEG Valuation			Descriptive Statistics $VMR = \|\varepsilon_{RIM}\| / \|\varepsilon_{PEG}\|$				
Year	α	β	Adjusted R^2	α	β	Adjusted R^2	Mean	Median	25th	75th	Std. Dev.
1997	6.40***	1.95***	0.82	8.82***	0.85***	0.66	0.78***	0.76***	0.35	1.85	6.35
1998	5.62***	2.44***	0.75	11.61***	0.89***	0.49	0.73***	0.72***	0.32	1.62	6.30
1999	5.78***	2.46***	0.63	7.29***	1.17***	0.51	0.90***	0.91***	0.43	1.93	6.03
2000	24.71***	1.70***	0.14	13.59***	1.08***	0.24	1.22***	1.16***	0.70	2.00	7.02
2001	15.70***	1.94***	0.36	18.52***	0.81***	0.30	1.12***	1.11***	0.63	1.98	7.27
2002	11.21***	1.63***	0.62	14.64***	0.85***	0.52	1.05**	1.04**	0.50	2.06	7.43
2003	3.57***	1.60***	0.69	9.95***	0.85***	0.54	0.96*	0.97*	0.43	2.10	7.03
All Years	12.74***	1.76***	0.41	12.68***	0.92***	0.40	0.99	1.01	0.48	1.98	6.91

Notes:
This panel 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 inferred valuation model use, defined as the ratio *VMR* ($= |\varepsilon_{RIM}| / |\varepsilon_{PEG}|$), 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 one denote inferred RIM model use whereas values greater than one 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 denoted as *, **, and *** for rejection at the 0.10, 0.05, and 0.01 level, respectively. Significance levels for *t*-tests (sign tests) of the null hypothesis that the mean (median) *VMR* equals one are similarly denoted.

TABLE 2 (Continued)

Panel B: Inferred valuation model use (*VMR)* by price target profitability and stock recommendation

Implied Price Target Profitability (*PT/P*) Portfolio				Buy/Sell Stock Recommendation			
Category	N	Mean *VMR*	Median *VMR*	Category	N	Mean *VMR*	Median *VMR*
5 (Most favored)	4,462	0.85***	0.92***	Strong Buy	7,300	0.92***	0.97**
4	4,919	0.97	0.99	Buy	7,288	1.01	1.03**
3	5,175	1.03	1.02	Hold	3,896	1.12***	1.09***
2 (Least favored)	5,103	1.05**	1.07***	Sell	250	1.05	1.08*
1 (Disfavored)	1,543	1.13***	1.12***	Strong Sell	70	0.96	1.02
All categories	21,202	0.99	1.01		18,804	1.00	1.02

Notes:
This panel reports summary statistics for inferred valuation model use (*VMR*), as defined in panel A, grouped according to the implied profitability of analysts' price targets (*PT/P*) and by their Buy/Sell recommendations. Sample 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 (category 2 through 5, where 5 denotes "most favored" stocks) based on the population of price targets in Table 1. We require each Buy/Sell recommendation to be current in the fourth month after the firm's fiscal year end. Significance levels for *t*-tests (sign tests) of the null hypothesis that the mean (median) *VMR* equals one are denoted as *, **, and *** for rejection at the 0.10, 0.05, and 0.01 level, respectively.

TABLE 3
Price target investment performance and valuation model use.

		Price Target Implied Return Category (*PT/P*<1 and then *PT/P* Quartiles)					
		Disfavored	Least favored			Most favored	
	N	1	2	3	4	5	MF - D
Mean *BHAR*	21,202	2.07	-1.42**	0.18	2.20**	5.00***	2.93**
Mean Implied Return	21,202	-10.02	9.05	20.34	31.48	61.80	71.82
Valuation Model Use Portfolio							
1 (Favors RIM)	3,507	-4.67	-2.79*	3.08	8.23**	10.46***	15.13**
2	3,511	3.22	-0.38	0.03	2.59	4.61*	1.40
3	3,511	2.39	-1.70	-0.30	1.49	9.34***	6.94
4	3,556	5.70*	-0.68	-1.21	-0.37	2.17	-3.52
5	3,559	3.09	0.11	0.31	-1.10	6.06**	2.97
6 (Favors PEG)	3,558	0.80	-3.22***	-0.75	2.12	-4.64**	-5.44*
P1 – P6		-5.48	0.43	3.84	6.11	15.10***	

Notes:
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 portfolios are based on $VMR = (|\varepsilon_{RIM}| / |\varepsilon_{PEG}|)$ as described in Table 2. The six portfolios are centered at *VMR* = 1 and are formed by sorting observations where *VMR* is less (greater) than one into terciles each year. *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/P* 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 0.10, 0.05, and 0.01 level, respectively.

TABLE 4
Earnings forecast accuracy

	All I/B/E/S Analysts Covering Sample Firms				I/B/E/S Analysts Providing Price Targets				Mean
	Mean	Median	Std. Dev.	N	Mean	Median	Std. Dev.	N	Difference
Earnings Forecast Accuracy Quintile									
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***

Notes:
This table describes the conditional distribution of absolute one-year-ahead EPS forecast error (*AFE*, scaled by share price) for earnings forecast accuracy quintiles constructed from the I/B/E/S detail population of analysts who issue Buy/Sell recommendations for sample firms and for the subset of analysts who also provide price targets to First Call. Each firm-year is required to have at least 5 unique *AFE* value. 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 two-tailed between-sample *t*-tests of the null hypothesis of mean equality are denoted as *, **, and *** for rejection at the 0.10, 0.05, and 0.01 level, respectively.

TABLE 5
Valuation model use and earnings forecast accuracy

Panel A: Valuation model use within earnings forecast accuracy quintiles

		Valuation Model Use ($VMR = \|\varepsilon_{RIM}\| / \|\varepsilon_{PEG}\|$) Portfolio						
		Favors RIM					Favors PEG	
	N	1	2	3	4	5	6	Overall
Earnings forecast accuracy quintile								
1 (most accurate)	3,633	16%	16%	17%	17%	17%	17%	100%
2	5,241	16%	16%	17%	18%	16%	17%	100%
3	5,047	16%	17%	16%	17%	17%	17%	100%
4	4,433	17%	17%	16%	16%	17%	16%	100%
5 (least accurate)	2,848	18%	17%	17%	16%	17%	16%	100%
Mean *VMR*		0.12	0.47	0.80	1.22	2.01	7.88	
Population base rate		16.5%	16.6%	16.6%	16.7%	16.8%	16.8%	100%

Notes:
This panel describes the conditional distribution of inferred valuation model use ($VMR = |\varepsilon_{RIM}| / |\varepsilon_{PEG}|$) by earnings forecast accuracy (*AFE*) quintile for the sample of 21,202 analyst-firm-year observations. Each cell reports the proportion of analyst-firm-year observations in a particular *AFE* quintile that fall into each valuation model (*VMR*) portfolio where *VMR* Portfolio 1 favors RIM use and Portfolio 5 favors PEG use. The *VMR* six portfolios are centered at $VMR = 1$ and are formed by sorting observations where *VMR* is less (greater) than one into terciles each year. *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*.

TABLE 5 (Continued)

Panel B: Price target investment performance by earnings forecast accuracy quintile

		Price Target Implied Return Category (*PT/P*<1 and then *PT/P* Quartiles)					
		Disfavored	Least favored			Most Favored	
	N	1	2	3	4	5	MF - D
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 *BHAR* over all quintiles		2.35**	-1.13***	-0.14	2.58***	2.57***	

Notes:
This panel reports average 12-month buy-and-hold abnormal returns (*BHAR* as defined in Table 3) 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"). Hedged portfolio returns are computed for the difference between extreme *AFE* quintiles (Q1 minus Q5) or extreme *PT/P* 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 0.10, 0.05, and 0.01 level, respectively.

TABLE 6
The incremental effects on price target investment performance of valuation model use and earnings forecast accuracy

Panel A: Full sample regression.

Coefficient Estimates										
Intercept	*PT/P_rank*	*REC_rank*	*AFE_rank*	*VMR_rank*	*PT/P_rank x AFE_rank*	*PT/P_rank x VMR_rank*	*AFE_rank x VMR_rank*	*PT/P_rank x AFE_rank x VMR_rank*	Adjusted R^2	N
8.12***	-15.00***	-3.66*	-6.97**	-2.24	19.88***	9.50*	-3.35	6.74	2.0%	18,804

Notes:
This panel reports the results obtained from buy-and-hold annual abnormal return (*BHAR* as defined in Table 3) 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. The variables *PT/P_rank*, *REC_rank*, *AFE_rank*, and *VMR_rank* are scaled to range between zero and one, and capture information about the ordinal ranking of the data. Specifically, *VMR_rank* equals one when the data imply use of the RIM valuation approach, *AFE_rank* is one for the quintile of most accurate EPS forecasts, *REC_rank* is zero when the analyst's recommendation is a "Strong Sell" and one when it is a "Strong Buy", and *PT/P_rank* is one for "most favored" stocks. Year fixed-effects are included but not reported. The availability of Buy/Sell recommendations limits the sample to 18,804 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 0.10, 0.05, and 0.01 level, respectively.

Panel B: Portfolio return estimates from the full sample regression model

		Incremental *BHAR* from Change in Portfolio Composition		
Benchmark Portfolio	*BHAR*	*VMR* = PEG	*AFE* = Least accurate	*VMR* = PEG and *AFE* = Least accurate
PT/P = Most favored, *AFE* = Most accurate, *VMR* = RIM	16.68***	-10.66***	-16.30***	-23.57***
PT/P = Disfavored, *AFE* = Most accurate, *VMR* = RIM	-4.44**	5.58*	10.32***	12.55***

Notes:
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 0.10, 0.05, and 0.01 level, respectively.

TABLE 6 (Continued)

Panel C: Portfolio return estimates from *PT/P* category regression models

			Incremental *BHAR* from Change in Portfolio Composition		
Benchmark Portfolio	*PT/P* Group	*BHAR*	*VMR* = PEG	*AFE* = Least accurate	*VMR* = PEG and *AFE* = Least accurate
VMR = RIM, *AFE* = Most Accurate	1 (Most favored)	34.63***	-12.05***	-17.22***	-22.60***
VMR = RIM, *AFE* = Most Accurate	2	17.44***	-6.91**	-8.36**	-14.54***
VMR = RIM, *AFE* = Most Accurate	3	-4.46	0.30	-1.68	-4.97**
VMR = RIM, *AFE* = Most Accurate	4 (Least favored)	-0.86	0.12	-1.77	1.61
VMR = RIM, *AFE* = Most Accurate	5 (Disfavored)	-9.32**	5.22	15.79***	16.93***

Notes:
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 0.10, 0.05, and 0.01 level, respectively.