JBFA Journal of Business Finance & Accounting

Journal of Business Finance & Accounting, 38(1) & (2), 119–144, January/March 2011, 0306-686X
doi: 10.1111/j.1468-5957.2010.02223.x

The Use of Earnings Forecasts in Stock Recommendations: Are Accurate Analysts More Consistent?

Andreas Simon and Asher Curtis*

Abstract: We examine how analysts' conflicting incentives to be either accurate or optimistic affect their choice to generate stock recommendations with rigorous valuation models or growth-based heuristics. Consistent with prior research the average analyst recommendation is negatively associated with rigorous valuation models and positively associated with growth-based heuristics, we document that these associations are weakest for the most accurate analysts and strongest for the least accurate analysts. We also find evidence consistent with consistency between recommendations and valuation models underlying the positive future returns from trading on the most accurate analysts' recommendations. Our results are consistent with reputation incentives to be accurate mitigating the use of optimistic growth-based models in generating stock recommendations.

Keywords: forecast accuracy, fundamental valuation, stock recommendations, analyst reputation

1. INTRODUCTION

Analysts face conflicting trade-generating incentives and must trade off the short-term incentive to optimistically bias forecasts and recommendations with the long-term incentive to build their own reputation through accurate forecasts and recommendations (Hayes, 1998; Hong and Kubik, 2003; Irvine, 2001; and Jackson, 2005). Bradshaw (2004) finds that analysts appear to generate their stock recommendations using growth-based heuristics, a finding that suggests that the need to be optimistic is, on average, the dominant incentive. We examine whether variation in individual

*The authors are, respectively, from the Orfalea College of Business, California Polytechnic State University and David Eccles School of Business, The University of Utah. This paper is related to work done by Andreas Simon in his Ph.D. dissertation at the University of Queensland. The authors gratefully acknowledge the helpful comments from an anonymous referee, Brian Cadman, Peter Clarkson, Russ Lundholm, Sarah McVay, Brian Rountree (AAA Annual Meeting Discussant), Irene Tutticci, Martin Walker (editor), participants at the University of Utah's Wednesday research group, brown bag participants at the University of Michigan, seminar participants at ESADE Business School, Bocconi University, University of New South Wales, and the 2010 AAA Annual Meeting. All errors remain the responsibility of the authors. (Paper received December 2008, revised version accepted August 2010)

Address for correspondence: Asher Curtis, David Eccles School of Business, University of Utah, 1645 East Campus Center Drive, Salt Lake City, UT 84112, USA.
e-mail: asher.curtis@business.utah.edu

analysts' incentives affects individual analysts' reliance on growth-based heuristics when generating their stock recommendations.

Specifically, we contribute new empirical evidence on whether reputation incentives appear to mitigate the use of growth-based heuristics in supporting analysts' stock recommendations by examining variation in accuracy at the individual analyst level. Following Jackson (2005), we consider analyst accuracy to be a proxy for analysts focusing on building their reputation. We expect analysts choosing to build their reputation (i.e., more accurate analysts) to rely on rigorous valuation models to generate more profitable stock recommendations. Conversely, we expect analysts choosing to be optimistic (who are therefore less accurate) to rely on growth-based heuristics when generating their recommendations, to the extent that these heuristics allow for a more optimistic recommendation.[1]

In general, our results appear consistent with Bradshaw (2004) in that the average analyst recommendation is negatively associated with rigorous valuation models and positively associated with growth-based heuristics.[2] Our contribution is to document that these associations are weakest for the most accurate analysts and strongest for the least accurate analysts. We measure analyst accuracy using both short-term and long-term earnings forecast accuracy, as analysts choosing to build their reputations have a longer-term focus. Our results are robust to the measurement of relative accuracy within two peer groups. Our primary analysis uses only firms for which there are at least three analysts following the same firm. This choice results in a smaller sample size but controls for firm-specific effects that could affect both the accuracy of an analyst's forecast and an analyst's valuation model choice. We also provide a broader sample where we consider relative accuracy of the individual analyst in the pool of analysts following firms in the same industry. In this group, similar to Demirakos et al. (2009), we control for differences in the firm's volatility of earnings to control for the firm-specific variation in the difficulty of forecasting future earnings.

We then examine the economic significance of consistency between individual analysts' recommendations and valuation models using individual analysts' inputs. Prior literature is mixed on the usefulness of analysts' recommendations. Some studies document that selecting stocks based on analysts' recommendations yields either insignificant or negative returns, while selecting stocks based on valuation models using analysts' inputs yields positive returns (Bradshaw, 2004; and Barniv et al., 2009a). Loh and Mian (2006), however, find that the recommendations of the most accurate analysts are positively associated with future returns. We find evidence consistent with a significant difference in the profitability of buy and sell recommendations of most accurate analysts when recommendations are aligned with rigorous valuation models. The least accurate analysts, conversely, do not yield profitable buy or sell recommendations when their recommendations are aligned with rigorous valuation models. For both the most and least accurate analyst groups, we find no profitability when recommendations are consistent with growth-based heuristics or when the

1 In additional analysis not tabulated here, we find that our measure of least accurate forecasts is correlated at 0.84 with an indicator of the most optimistic forecasts.

2 The association between recommendations and growth-based heuristics has declined but has not been completely eliminated, following the Global Research Analyst Settlement and other regulations aimed at reducing conflicts of interest in the investment banking industry (Barniv et al., 2009a; and Chen and Chen, 2009). Similar results are also observed outside of the US capital markets, but only in countries where the capital markets are relatively active (Barniv et al., 2009b), suggesting that analysts' incentives to generate trade with optimism are stronger in more active markets.

recommendations are not consistent. These results suggest that consistency between recommendations and valuation models helps explain the positive future returns from trading on the most accurate analysts' recommendations.

We also examine the robustness of our results to our definition of accuracy. Consistent with forecast accuracy being a good proxy for reputation building, we find little difference between the most accurate forecasters and All-Star analysts when examining the association between recommendations and valuation models. We also provide some evidence that rigorous valuation models are positively correlated with the recommendations of accurate analysts when we control for long-term growth. To mitigate concerns that our results could be due to potentially correlated omitted factors such as the information gathering capacity of the analyst, private information, and (mispriced) non-financial information, we examine the links between changes in stock recommendations and changes in valuation models. While our results are weaker statistically in this specification, the evidence is in the same vein as our main results.

Our contribution can be summarized as follows. Overall, our results help to reconcile conflicting views on the usefulness of analysts' stock recommendations. Consistent with prior research, our results suggest that on average there is a strong bias towards recommending stocks based on growth-based heuristics rather than rigorous valuation models. Our results for the most accurate forecasters are consistent with reputation incentives mitigating the use of optimistic growth-based models in place of rigorous valuation models in generating stock recommendations. While reputation incentives do not appear to align the recommendations of analysts with more rigorous valuation approaches, in general, our results do suggest that reputation concerns have an economically and statistically significant effect on the use of growth-based models.

2. PRIOR RESEARCH AND HYPOTHESES

(i) Prior Research

Previous studies have extensively examined stock recommendations, earnings forecast accuracy, and valuation models using analyst forecasts, but generally in isolation. As we investigate whether reputation concerns affect the relation between stock recommendations and valuation models using analyst forecasts as inputs, we focus on the more recent literature that examines the relation among analyst provided information. Broader reviews of the literature are provided by Brown (1993) and Bradshaw (2010).

Early work investigating the inputs used to recommend stocks involved surveys of analysts and content analysis of their reports. In his survey, Block (1999) finds that analysts seldom use discounted cash-flow analysis. Similarly, content analyses of analysts' reports provide little evidence that analysts use discounted cash-flow analysis to support recommendations (Asquith et al., 2005; Bradshaw, 2002; and Breton and Taffler, 2001). Instead, Bradshaw (2002) finds that analysts tend to support their recommendations with heuristics such as earnings growth and the price-to-earnings growth (PEG) ratio.

Bradshaw (2004) provides large-sample empirical evidence consistent with analysts' recommendations reflecting the information in heuristics such as the PEG ratio rather than more rigorous valuation models. Specifically, he finds a positive association between recommendations and the PEG ratio, and a negative association between recommendations and the residual income-to-price ratio. He also provides evidence that analysts' recommendations are positive when their long-term growth expectations are high.[3] Further evidence suggests that this result is not limited to the US market but extends to countries with more active capital markets (Barniv et al., 2009b), and that the US market has seen increased use of rigorous valuation models following the Global Research Analyst Settlements (Barniv et al., 2009a).

Part of the optimistic bias could be due to the selection of firms covered by analysts, as analysts' incentives to gather and provide information are strongest for stocks that are expected to perform well (Hayes, 1998). Ertimur et al. (2008) provide empirical evidence of analysts initiating recommendations following high returns and prior growth, consistent with the model in Hayes (1998). Analysts' recommendations also appear to be inconsistent with future returns expected from low book-to-market stocks and high price momentum stocks (Stickel, 1995; Finger and Landsman, 1998; and Jegadeesh et al., 2004). Ertimur et al. (2007) provide evidence that analysts' incentives conflict with those of investors due to investment banking relationships. Recent studies by Cowen et al. (2006), Ke and Yu (2009) and Mokoaleli-Mokotelli et al. (2009) suggest that additional behavioral and trading commission based incentives affect analysts' recommendations. Following Jackson (2005), Rountree (2009) suggests that analysts' trade-based incentives may also contribute to variation in the optimistic bias. Collectively, these studies suggest that recommendations are generally driven by factors other than identifying undervalued stocks using fundamental analysis.

Recent research, however, has shown that there are exceptions based on an individual analyst's accuracy. Specifically, Loh and Mian (2006), Ertimur et al. (2007) and Gleason et al. (2009) provide evidence that stock recommendations are more profitable for analysts who are better at forecasting short-term earnings. Using a database of analysts' stock reports, Demirakos et al. (2009) find that analysts' price-to-earnings based models outperform discounted cash-flow models in target price accuracy and that this effect is mitigated by the difficulty of the valuation task. Presenting evidence consistent with decreased use of less rigorous valuation approaches, Glaum and Friedrich (2006) document increased use of discounted cash flow analysis in European telecommunication analysts' reports after the late 1990s. Collectively, these studies suggest that individual analysts' incentives vary significantly.[4]

Our study contributes to this literature by examining the association between analysts' recommendations and valuation models based on differences in individual analysts' incentives. Specifically, we examine how this association is affected by the conflicting desires to provide optimistic information to generate trading volume and to provide accurate information to build their own reputations.

3 There is considerable evidence that long-term growth estimates are optimistically biased (La Porta, 1996; Harris, 1999; and Dechow et al., 2000), so it is possible that analysts use these forecasts to *ex post* justify their recommendations that are also upwardly biased.

4 Additional evidence that analysts' incentives may be important is found in Deloof et al. (2009), who study the valuation choices of French underwriters and document that they use discounted cash flow analysis to support IPO offer prices, and that All-Star unaffiliated underwriters in the US markets tend to be less optimistically biased and less willing to follow a firm in the period following an IPO with significant underpricing (Bradley et al., 2009). Interview research by Imam et al. (2008) also suggests a shift among UK analysts towards the use of more rigorous valuation models. A concurrent paper also suggests a role for analysts' accuracy, through consistency (see Brown and Huang, 2010).

(ii) Hypothesis Development

Generally, analysts are expected to undertake an equity valuation process through which they collect information and use it to forecast future earnings and earnings growth. Then analysts may combine their forecast information with additional inputs into a valuation model, and by comparing this estimate to market price, produce a recommendation for the stock (Schipper, 1991). Assuming such a process, we expect individual analysts' incentives to affect the inputs used to generate a stock recommendation. Specifically, a more accurate forecast provides a better estimate of fundamental value that is more likely to help predict future returns (Frankel and Lee, 1998; and Lundholm and Sloan, 2007). Over time, analysts with more accurate forecasts and more profitable recommendations have better reputations and are more likely to be promoted and receive higher compensation (Stickel, 1992; Mikhail et al., 1999; Hong and Kubik, 2003; Jackson, 2005; and Groysberg et al., 2008).[5]

Bradshaw (2004) provides evidence consistent with a disconnect somewhere in the process of converting forecasts into recommendations. Ertimur et al. (2007) point out three potential sources: (1) that analysts' reported forecasts differ from their actual computed forecasts, (2) that analysts' reported recommendations are not based on their discounted cash-flow estimates relative to price (i.e., they are influenced by other factors), and (3) that earnings are not a value-relevant input in valuation. In addition to these analyst- and firm-level variables, Jackson (2005) suggests a potential analyst-specific reason for a disconnect: that individual analysts weight short-term and long-term trade generating incentives differently.

While forecasting accuracy does not appear to be directly compensated (Groysberg et al., 2008), to the extent that highly reputable analysts such as All-Stars are better paid, there are incentives to build reputation over the long run. Jackson (2005) suggests that individual analysts can build their reputations through more accurate earnings forecasting and stock recommendations. As a more accurate forecast more readily translates into a better estimate of fundamental value (Lundholm and Sloan, 2007), we hypothesize that reputation-building analysts' recommendations will be more aligned with rigorous valuation models and less aligned with growth-based heuristics to maximize the possibility that their recommendations are profitable.[6]

Absent other competing reasons for recommending a stock, we expect that reputation-building analysts, as proxied by forecast accuracy, will recommend stocks based on the disparity between their value model estimates and the prevailing market price. Conversely, when analysts have greater incentives to produce optimistic recommendations and forecasts than to build their own reputations, we expect that their recommendations will be more aligned with growth-based heuristics. We do not claim that less accurate analysts are incapable of forming rigorous valuation models using cash-flow analysis, but given the well known optimistic bias in analysts' forecasts (Stickel, 1995), we expect that optimistic analysts will favor valuation approaches that

5 Additional examples of a possible reputation effect come from prior research examining *Institutional Investor* All-American Research Team analysts (hereafter, All-Star Analysts). These analysts have more accurate earnings forecasts, and their forecasts have a greater effect on market prices (Stickel, 1992; and Park and Stice, 2000).

6 It is well known that future returns relate positively to rigorous valuation models and negatively to growth-based heuristics (e.g., Frankel and Lee, 1998; and Bradshaw, 2004).

highlight expected growth as the primary determinant of a favorable recommendation.[7] Stated as a hypothesis:

H_1: The stock recommendations of individual analysts with the most accurate forecasts will be significantly less correlated with simple heuristics (such as the PEG ratio) and significantly more correlated with rigorous valuation approaches than their less accurate peers.

Several factors work against our finding evidence that supports our hypothesis. As noted earlier, in his survey, Block (1999) finds that analysts use present value techniques less frequently than one might expect. Similarly, Bradshaw (2002) and Asquith et al. (2005) find few mentions of present value techniques when performing content analyses of analysts' reports. In addition, Bradshaw's (2004) evidence on the linkage between stock recommendations and earnings-based valuation models shows a negative correlation between stock recommendations and earnings-based valuation models at the consensus level.

3. SAMPLE SELECTION AND MEASUREMENT OF VARIABLES

(i) Data Sources and Sample Selection

To test our predictions, we require data on analyst accuracy, stock recommendations, forecasts of earnings and earnings growth, book-values, prices and returns. We source our data from the unadjusted I/B/E/S detail history files, unadjusted I/B/E/S actual file, CRSP and Compustat. Following Hong and Kubik (2003), we focus our analysis on December year-end firms to avoid the problem of overlapping horizons. For each individual (non-anonymous) analyst, we use the last available forecast prior to June 30 that is issued or updated after the earnings announcement from the prior fiscal year-end. Our sample ends in 2002 due to the requirement of five years of actual data to calculate long-term growth forecast errors.

Using this sample formation, we begin with 39,738 and end with 6,732 analyst-firm observations. Table 1 summarizes the reasons for the sample reduction, most of which is due to: (i) the lack of actual long-term growth data on I/B/E/S (2,801), (ii) the lack of recommendation and/or short-term earnings information (10,115), (iii) the requirement that each firm in the main sample have at least three distinct analysts covering the stock (8,343), and (iv) the exclusion of the off-diagonal analyst accuracy group observations (11,235).[8]

7 While we primarily use the absolute value in our analysis (and hence the least accurate analysts), we find similar results when we use the most optimistic analysts. The correlation between low accuracy and high optimism is high at 0.84, and the correlation between high accuracy and high optimism is −0.92. In results not tabulated here, we find that using either low accuracy or high optimism as a proxy for the non-reputation-building group provides similar results.

8 Where the diagonal is defined as the same accuracy groups on both short- and long-term dimensions (i.e., high short-term and high long-term accuracy) and the off-diagonal is defined as those firms that are categorized into different groups (i.e., low short-term and high long-term accuracy). We consider all 17,967 observations (both on- and off-diagonal groups) in our sensitivity analysis, as well as 9,765 observations with at least one analyst following the stock.

Table 1
Sample Selection Criteria

Starting sample of long-term EPS growth forecasts:	
December year-end firms with (non-anonymous) individual analyst forecasts issued after the earnings announcement and prior to June 30.	39,738
Less: Observations with missing data on I/B/E/S of actual long-term EPS growth	(2,801)
	36,937
Less: Observations without a matching one-and two-year earnings forecast, and at least one recommendation outstanding for the return accumulation year	(10,115)
	26,822
Less: Observations with extreme long-term EPS growth errors	(512)
	26,310
Less: Observations with fewer than three distinct analysts	(8,343)
	17,967
Less: Observations not in the hi,hi; med,med; and lo,lo groups based on both one-year ahead and long-term EPS growth forecast accuracy	(11,235)
Final sample	6,732

Notes:
In this table we report the reduction in the sample size due to our data requirements. The raw long-term EPS growth forecasts are from the I/B/E/S Detail History File. Actual long-term EPS growth is provided by the I/B/E/S Actual Files. One- and two-year ahead earnings forecasts and recommendations data are from the I/B/E/S Detail History and Recommendation File. The long-term EPS growth forecasts and earnings forecasts cover the period of January 1994 to December 2001, whereas the corresponding recommendations cover the period from October 1993 to March 2002.

(ii) Measurement of Analyst Accuracy

We measure analyst accuracy using (i) each analyst's short-term (one-year earnings per share, EPS) forecast and (ii) each analyst's long-term earnings growth forecast (hereafter, LTG, which is generally considered a five-year forecast of percentage growth in EPS). As reputation building is not simply a short-term endeavor, and long-term growth estimates are important in estimating discounted cash-flows (Lundholm and O'Keefe, 2001), the ability to accurately forecast long-term earnings growth appears to be a crucial input into linking discounted cash-flow estimates to stock recommendations. In addition, Frankel and Lee (1998) find that the most optimistic long-term growth forecasts are associated with higher short-term forecast errors, suggesting that short- and long-term analyst accuracy are correlated. Accordingly, our primary measure of analyst accuracy is based on combining both relative short-term and relative long-term forecast accuracy.

We calculate short-term accuracy based on the one-year forecast error of EPS:

$$\mathrm{ST}Acc_{ijt} = \left| \frac{Actual_{jt} - Forecast_{ijt}}{Actual_{jt}} \right|, \tag{1}$$

where $\mathrm{ST}Acc_{ijt}$ is analyst *i's* absolute EPS forecast error for firm *j* of EPS in year *t*, $Actual_{jt}$ is the actual EPS for firm *j* in year *t*, and $Forecast_{ijt}$ is the one-year ahead EPS forecast for analyst *i* for firm *j* in year *t*. For each firm-year, analysts are ranked into three groups by $\mathrm{ST}Acc_{ijt}$.

Following Dechow et al. (2000), we measure long-term analyst forecast accuracy as the absolute difference between the actual average annualized growth in earnings over five years minus forecasted growth (LTG).[9] Consistent with prior research, we do not scale this measure as I/B/E/S reports LTG as annualized percentages (Bradshaw et al., 2006; and Dechow et al., 2000):

$$\mathrm{LT}Acc_{ijt} = \left|Actual_{jt} - Forecast_{ijt}\right|, \tag{2}$$

where $\mathrm{LT}Acc_{ijt}$ is analyst *i's* absolute LTG forecast error for firm *j* issued in year *t*, $Actual_{jt}$ is the actual average annualized percentage growth in EPS from $t+1$ to $t+5$, and $Forecast_{ijt}$ is the corresponding forecast, issued by analyst *i* for firm *j* in year *t*. For each firm-year, analysts are ranked on $\mathrm{LT}Acc_{ijt}$ into three groups.[10]

As each analyst-firm observation is independently assigned to three groups based on short-term accuracy and to three groups based on long-term accuracy, we have nine portfolios based on the combination of these measures. We focus on analysts assigned to the three accuracy groups along the diagonal; that is, analysts who are most accurate on both short-term and long-term dimensions, average in their accuracy on both dimensions and least accurate on both dimensions. While this design choice limits our sample size by including only the observations on the diagonal of possible combinations, it allows us to examine a higher power test by focusing on the extremes, which are more likely to capture the reputation- and optimism-based incentives.[11]

(iii) Measurement of Earnings-Based Valuation

We use the residual income model (Ohlson, 1995) to calculate our earnings-based valuation estimates. Following Bradshaw (2004), we estimate residual income for the next five years and add a terminal value, calculated at the end of the fifth forecast year as follows:

$$V_{it} = \mathrm{BVPS}_t + \sum_{\tau=1}^{5} \frac{E_t[\mathrm{EPS}_{t+\tau} - r\mathrm{BVPS}_{t+\tau-1}]}{(1+r)^\tau} + \frac{E_t[\mathrm{TV}_{t+5}]}{(1+r)^5}, \tag{3}$$

where V_{it} is the intrinsic value estimate of firm *i* at time *t*, BVPS_t is the book value per share (Compustat #60/#25), E[.] is the expectations operator given the information set at *t*, and $\mathrm{EPS}_{t+\tau} - r\mathrm{BVPS}_{t+\tau-1}$ is residual income for forecast year $t + n$. We use individual analysts' EPS forecasts from I/B/E/S for years $t+1$ and $t+2$. EPS forecasts for $t+3$, $t+4$ and $t+5$ are extrapolated using the individual analysts' LTG forecasts applied to the EPS forecasts at $t+2$ (and compounded thereafter). Future book values are extrapolated from historical book values based on the clean surplus relation. The required rate of return, *r*, is based on Fama and French (1997) three-factor estimates of the industry-specific equity risk premium plus the risk-free rate, provided by 30-day Treasury bill yield, in effect for the month prior to the release of the forecast and

9 I/B/E/S long-term growth estimates are generally considered to estimate the growth in earnings over a five-year period; I/B/E/S annualizes each individual analyst's LTG forecast and converts it into a percentage. As the adjustments and calculations that I/B/E/S undertakes are not perfectly clear, we include only observations for which I/B/E/S provides an 'actual' LTG figure in order to reduce the introduction of additional errors into our analysis.

10 If we restricted the sample to firms with at least five analysts covering the stock (to obtain quintile measures more commonly used in prior research), our sample size would be reduced to 379.

11 Including all firms with at least three analysts yields 17,967 observations; we present analysis including these 'off-diagonal' observations in the regression in Section 5 (see Table 7, Panel B). We also examine short-term and long-term accuracy separately and obtain qualitatively similar results (not tabulated here).

stock recommendation. It is well known that the estimate of value is highly sensitive to assumptions made about the terminal value (TV). We therefore provide three different estimates of TV in our analysis.

Our first estimate is based on allowing residual income to fade to zero. This specification follows directly from Bradshaw (2004) and is based on estimating an autoregressive coefficient for residual income:

$$\mathrm{RI}_t = \alpha + \omega \mathrm{RI}_{t-1} + \varepsilon_t, \tag{4}$$

where $\mathrm{RI}_t = \mathrm{EPS}_t - r\mathrm{BVPS}_{t-1}$ and α and ω are the estimated regression coefficients, which is estimated by industry for all Compustat firms with available data.[12]

This results in the following expression for the terminal value:

$$E_t[\mathrm{TV}_{t+5}] = \frac{\omega}{1 + r - \omega} E_t[\mathrm{RI}_{t+5}]. \tag{5}$$

We label the resulting value estimate using the terminal value in equation (5) as V_{Fade}. Consistent with Bradshaw (2004), our second terminal value assumes that residual income persists in perpetuity at the rate r:

$$E_t[\mathrm{TV}_{t+5}] = \frac{E_t[\mathrm{RI}_{t+5}]}{r}. \tag{6}$$

We label the resulting value estimate using the terminal value in equation (6) as V_{Perp}. The third terminal value calculation controls for continuing growth in abnormal earnings beyond the earnings forecast horizon. Thus, we also calculate the terminal value incorporating the information in each individual analyst's estimate of long-term growth:

$$E_t[\mathrm{TV}_{t+5}] = \frac{E_t[\mathrm{EPS}_{t+6} - r\mathrm{BVPS}_{t+5}]}{(r - \mathrm{LTG}_t)(1 + r)^5}, \tag{7}$$

where EPS_{t+6} and BVPS_{t+5} are calculated consistently with the approach used in equation (2). We require LTG to be less than the required rate of return in order to calculate this terminal value.[13] We label the resulting value estimate as V_{LTG}.

Following Bradshaw (2004), we also assess whether recommendations are consistent with growth-based heuristics by examining the price-to-earnings and growth, or PEG, ratio. Survey research (Block, 1999) and content analysis of analyst reports (Bradshaw, 2002; and Asquith et al., 2005) find that present value techniques are not as widely used in practice as they are in theory. In particular, a valuation heuristic, the PEG ratio, is frequently used in the analyst community. Following Bradshaw (2004), we implement

12 Realized residual income is computed as annual income before extraordinary items (Compustat data item #18) cleansed of special items (item #17) assuming a 35% tax rate, less a capital charge based on Fama and French (1997) industry estimates multiplied by beginning equity book value (item #60), all divided by beginning market value (item #25 multiplied by item #199). Income is adjusted for special items to be consistent with forecasted earnings, since analysts typically do not forecast special or extraordinary items (Bradshaw and Sloan, 2002).

13 While this restriction removes the most optimistic LTG forecasts, we still find significant variation in optimism.

PEG as:

$$V_{\mathrm{PEG}} = E_t[\mathrm{EPS}_{t+2}] \times \mathrm{LTG}_t \times 100, \tag{8}$$

where V_{PEG} is the *pseudo*-price target, which divided by price yields the PEG ratio; EPS_{t+2} is the analyst's two-year ahead earnings forecast; and LTG is the analyst's projection of long-term annual earnings growth. In our analysis, we scale all of the value estimates (V_{Fade}, V_{Perp}, V_{LTG} and V_{PEG}) by market price (P) to form a distribution of V/P ratios that provide a measure of the relative attractiveness of the stock.

4. EMPIRICAL ANALYSES

(i) Descriptive Statistics

Table 2 reports descriptive statistics on variables used in the regressions. Panel A of Table 2 reports the distribution of valuation estimates to price. Mean V_{Fade}/P is 0.57 and mean V_{Perp}/P is 0.83. The mean V_{LTG}/P is 0.73. The difference in the means of the three residual income to price ratios demonstrates the importance of terminal values in the calculations and emphasizes that without a perfect measurement of the terminal value, it is beneficial to consider all three estimates in our analysis (Lundholm and O'Keefe, 2001; and Penman, 2001). In addition, all three residual income-based value estimates are less than one on average, suggesting that analysts' recommendations are unlikely to be based strictly on such valuations, as we would then expect sell recommendations, on average. Conversely, the mean PEG ratio is 1.26 and significantly greater than one (p-value < 0.001), which is more consistent with the provision of 'buy' recommendations, on average.

To ascertain the economic significance of the differences in forecast accuracy across the three accuracy groups, we report the summary statistics of the average firm-level $\mathrm{ST}Acc_{ijt}$ and $\mathrm{LT}Acc_{ijt}$ across terciles in Panel B of Table 2. As in Loh and Mian (2006), we compute the mean scaled absolute forecast error across analysts for each firm-year in a given tercile, and then average across firm-years within each tercile. When we sort our observations based on accuracy, we have 1,900, 2,570 and 2,262 analyst-firm-year observations in the high accuracy, average accuracy, and low accuracy group, respectively.[14] The overall mean $\mathrm{LT}Acc_{ijt}$ is 18.81%, and the median is 12.72%, suggesting that LTG forecasts deviate widely from realized earnings growth rates. The mean and median LTG forecast error is smaller in the most accurate tercile, by construction. Mean $\mathrm{ST}Acc_{ijt}$ is 0.15, about half that of Loh and Mian (0.289), which suggests that our sample analysts (requiring LTG forecasts) are more accurate than the average analyst on I/B/E/S. We present correlations between the primary variables of interest for the most (least) accurate analysts in Panel C (Panel D). For the most accurate analysts we find that the correlation for the rigorous valuation model-to-price ratios and recommendation is negative and significant, consistent with analysts issuing the most (least) favorable recommendations for stocks with the lowest (highest) valuation relative to price. In contrast to Bradshaw

14 The proportion of observations within each cohort deviates from one-third because there are many instances where one firm is covered by a number of analysts not divisible by 3. When the observations are tied, we put them into the lower group (i.e., for a group of 5 analysts, if the 4$^{\text{th}}$ and 5$^{\text{th}}$ most accurate observations are tied, they are both assigned to the least accurate group). This means that a disproportionate number of observations are grouped in the middle and lower tercile.

Table 2

Descriptive Statistics of Variables used in the Regressions

Panel A: Valuation Model to Price (N = 6,732)

Model	*Mean*	*Median*	*Std. Dev.*	*P10*	*P90*
V_{Fade}/P	0.57	0.47	0.42	0.19	1.07
V_{Perp}/P	0.83	0.71	0.86	0.23	4.24
V_{LTG}/P	0.73	0.19	1.64	0.11	1.03
V_{PEG}/P	1.26	1.20	0.63	0.81	1.44
LTG	17.40	14.70	10.30	7.47	65.00

Panel B: Absolute Long-Term and Short-Term Earnings Accuracy Averages within each Tercile (N = 6,732)

	N	*Mean*	*Median*	*Std. Dev.*
LTG forecast accuracy terciles (LT*Acc*)				
A1 (High accuracy)	1,900	13.91	7.51	15.87
A2	2,570	17.79	12.64	17.13
A3 (Low accuracy)	2,262	21.05	14.67	19.55
Overall	6,732	18.81	12.72	18.39
EARN forecast accuracy terciles (ST*Acc*)				
A1 (High accuracy)	1,900	0.09	0.04	0.19
A2	2,570	0.14	0.06	0.29
A3 (Low accuracy)	2,262	0.18	0.08	0.37
Overall	6,732	0.15	0.06	0.32

Panel C: Correlation for Most Accurate Analysts (N = 1,900)

	REC	V_{Fade}/P	V_{Perp}/P	V_{LTG}/P	V_{PEG}/P	*LTG*
REC	–	−0.19	−0.33	−0.38	0.06¢	0.15
V_{Fade}/P	−0.27	–	0.57	0.64	0.11	−0.10
V_{Perp}/P	−0.36	0.60	–	0.72	0.16	−0.08
V_{LTG}/P	−0.41	0.69	0.77	–	0.22	0.12
V_{PEG}/P	0.09¢	0.24	0.29	0.36	–	0.49
LTG	0.21	−0.18	−0.10	0.19	0.55	–

Panel D: Correlation for Least Accurate Analysts (N = 2,262)

	REC	V_{Fade}/P	V_{Perp}/P	V_{LTG}/P	V_{PEG}/P	*LTG*
REC	–	0.07¢	0.02¢	−0.08¢	0.36	0.45
V_{Fade}/P	0.09¢	–	0.48	0.40	0.35	−0.30
V_{Perp}/P	0.03¢	0.50	–	0.72	0.16	−0.08
V_{LTG}/P	−0.11¢	0.47	0.48	–	0.22	0.54
V_{PEG}/P	0.40	0.39	0.46	0.40	–	0.61
LTG	0.49	−0.48	−0.35	0.51	0.66	–

Notes:

In this table we report descriptive statistics for the variables used in our regressions. In Panel A we report the four proxies for rigorous valuation model (V_{ij}): we use the residual income model with a five-year horizon and the following terminal values mean-reverting towards the industry mean, V_{Fade}, a perpetuity V_{Perp}, and a growing perpetuity at the analyst's long-term growth rate, V_{LTG}. We also calculate two growth-based heuristics, V_{PEG}, which is two-year ahead forecasted earnings-per-share multiplied by LTG; and LTG, which is the analyst's forecast long-term earnings growth. The valuation model estimates are divided by P, which is price at the close on June 30 to form the valuation ratios. Panel B reports our reputation building incentives proxies. LTG (EARN) is the analysts' long-term earnings growth forecast (one-year earnings forecast), respectively. Observations are included in the most accurate group, A1, if the analyst is in the most accurate tercile for both short-term and long-term forecast accuracy; the middle group, A2, if the analyst is in the median tercile for both short-term and long-term forecast accuracy; and in the least accurate group, A3, if the analyst is in the least accurate tercile for both short-term and long-term forecast accuracy. Panel C and Panel D present Pearson (Spearman) correlations above (below) the diagonal. All correlations are significant at the 0.01 level. Insignificant variables are labeled with ¢

(2004), we find that recommendations have higher correlations with rigorous valuation model-to-price ratios than with growth heuristics, PEG and LTG. Although small, there is also a positive correlation between PEG and the rigorous valuation models.[15] For the least accurate analysts we find correlation for the rigorous valuation model-to-price ratios and recommendation is insignificant, whereas growth-based heuristics are positively correlated with recommendations. Untabulated statistics are consistent with prior research which documents that the distribution of recommendations is positively skewed (e.g., Stickel, 1995; and La Porta, 1996).

(ii) Tests of the Reputation-Building Hypothesis

In this section we examine whether the recommendations of analysts who appear to be building their reputation by providing more accurate forecasts are less aligned with growth-based heuristics and more aligned with rigorous valuation models. Following Bradshaw (2004), we examine the association between recommendations and valuation estimates based on their forecasts, though we implement this model using individual analyst forecasts:

$$Rec_{ij} = b_0 + b_1 V_{ij} + e_{ij}, \tag{9}$$

where Rec_{ij} is analyst j's recommendation for firm i. Following prior research, we code the recommendations in reverse (i.e., 5 = strong buy to 1 = strong sell) and our valuation estimates are all strictly positive, allowing us to interpret a positive b_1 coefficient as a consistent recommendation relative to the valuation model. Our independent variable of interest, V_{ij}, is a valuation model estimate using forecasts of analyst j for firm i (using V_{Fade}, V_{Perp}, V_{LTG}, V_{PEG}), and it is deflated by the market price per share on the day of the stock recommendation calculation or the undeflated long-term growth estimate (LTG).[16]

Our hypothesis is that more accurate forecasters will recommend stocks based more on rigorous valuation models and less on growth-based heuristics than their less accurate peers. We test this hypothesis by adding indicator variables for the most accurate and least accurate analysts:

$$Rec_{ij} = b_0 + b_1 V_{ij} + b_2(V_{ij} \times HiAcc_{ij}) + b_2(V_{ij} \times LoAcc_{ij}) + e_{ij}, \tag{10}$$

where V_{ij} is the valuation estimate (V_{Fade}, V_{Perp}, V_{LTG}, V_{PEG}) to price ratio or LTG; $HiAcc_{ij}$ is an indicator variable equal to 1 if the analyst is in the most accurate tercile based on both short-term and long-term forecast accuracy, and 0 otherwise; and $LoAcc_{ij}$ is an indicator variable equal to 1 if the analyst is in the least accurate tercile based on both short-term and long-term forecast accuracy, and 0 otherwise. As Demirakos et al.

15 We leave to future research the interesting question as to why PEG is not positively associated with future abnormal returns when it is correlated with rigorous valuation models that are positively associated with them. One possible explanation is that analysts also assess the riskiness of a stock through discount rate adjustments (see Kecskes et al. 2010), and PEG fails to adequately capture risk.

16 Our model differs slightly from that of Bradshaw (2004). He uses the consensus recommendation as the dependent variable in equation (9) and consensus forecasts to calculate measures of value as the independent variables. Whereas Bradshaw estimates the model for each of 12 fiscal months to control for systematic differences in earnings as analysts walk down their forecasts during the fiscal year, we are more concerned with the differences between the analysts and use a common cut-off at June 30 (Loh and Mian, 2006; and Sinha et al., 1997).

(2004) find that the use of valuation models by analysts differs among industries, and forecast accuracy is known to vary by industry, we present our regressions using a within firm design to control for this potential endogeneity concern.[17]

We report the summary regression results for equation (10) in Table 3. In Panel A, the association between recommendations and valuation techniques for the average forecaster is captured in b_1, and the sign of the association is consistent with Bradshaw (2004).[18] Specifically, the average analyst's recommendations are negatively associated with residual income valuations and positively associated with growth-based heuristics. For example, for the V_{Perp} model, $b_1 = -0.04$ (t-statistic $= -2.41$), but for long-term growth, LTG, $b_1 = 0.09$ (t-statistic $= 4.38$).

Extending the model of Bradshaw (2004) to incorporate individual analyst accuracy, we find that higher levels of analyst accuracy appear to mitigate the negative associations of recommendations with rigorous valuation models, while low levels of accuracy appear to accentuate the negative associations. Specifically, in all three residual income models, the coefficients on the interaction of more accurate analysts with rigorous valuation models are positive and significantly different from zero, suggesting a mitigation of the bias away from rigorous valuation models for this sub-group. Conversely, the coefficients on the interaction of less accurate analysts with rigorous valuation models are negative and significant, suggesting an accentuation of the bias away from rigorous valuation models for this sub-group. For example, in the V_{LTG} model, the interaction with $HiAcc_{ij}$ is positive and significantly different from zero, $b_2 = 0.03$ (t-statistic $= 2.61$), and significantly different from the $LoAcc_{ij}$ interaction ($b_3 = -0.03$) with an F-statistic of 9.37.

While these results do not suggest that accurate analysts' recommendations are positively associated with rigorous valuation models, they do suggest that the accurate analysts' recommendations are not negatively associated with rigorous valuation models, on average. This mitigation of the negative association is also economically significant. For example, in the V_{Perp} model, the bias is mitigated by 50% for the group of accurate analysts (as the sum of b_1 and b_2 equals -0.02) and accentuated by 225% for the group of the least accurate analysts (as the sum of b_1 and b_3 equals -0.13). If we exclude the V_{Fade} model, the sum of b_1 and b_2, which can be viewed as the total bias for accurate analysts, is not statistically different from zero, consistent with no evidence of a statistically significant bias away from rigorous valuation models in this group. While the magnitude of the mitigation and bias vary, the results do provide some evidence that the bias is completely mitigated in the group of most accurate analysts.

We also examine the association between recommendations and growth-based heuristics in Panel A of Table 3. Consistent with Bradshaw (2004), we find that growth-based heuristics are positively associated with analysts' recommendations. We also find, however, that the association is significantly greater for the least accurate forecasters.

17 We group analysts into accuracy cohorts as analysts cover different firms, even within the same industry. Because some firms' earnings are more difficult to forecast, sorting analysts on their forecast accuracy rank within firm assures that the analyst who produces the most accurate estimate of firm A performs as well as the analyst who produces the most accurate estimate of firm B, regardless of the actual forecast errors of the analysts for the two firms (see Hong et al., 2000 for a similar approach). As a robustness check, we examine industry-level accuracy and present the results in Section 5 (see Table 7, Panel A).

18 Note, however, that our coefficients and adjusted R^2s are lower than those reported in Bradshaw (2004). We believe that this is due to the additional heterogeneity of forecasts at the individual analyst level. In results not reported here, we confirm this conjecture by examining the mean of our individual analysts' recommendations and valuation model estimates, when we do this our results are qualitatively similar to those of Bradshaw (2004).

Table 3

Forecast Accuracy and the Association Between Stock Recommendations and Fundamental to Price Ratios

Valuation	b_0	b_1	b_2	b_3	*F-test* $b_1 + b_2 = 0$	*F-test* $b_2 = b_3$	*Adj.* R^2
Panel A: Individual Analysts' Accuracy Relative to Same Firm-Following Peers (N = 6,732)							
$Rec_{ij} = b_0 + b_1 V_{ij} + b_2(V_{ij} \times HiAcc_{ij}) + b_3(V_{ij} \times LoAcc_{ij}) + e_{ij}$							
V_{Fade}/P	2.67**	−0.11**	0.02*	−0.13**	10.77**	3.77**	0.023
	(83.17)	(−3.31)	(1.93)	(−2.01)	[< 0.01]	[0.01]	
V_{Perp}/P	2.63**	−0.04**	0.02**	−0.09**	1.09	10.2**	0.010
	(113.98)	(−2.41)	(2.44)	(−2.24)	[0.30]	[< 0.01]	
V_{LTG}/P	2.64**	−0.04**	0.03**	−0.03*	0.19	8.97**	0.056
	(121.44)	(−2.63)	(2.61)	(−1.99)	[0.66]	[< 0.01]	
V_{PEG}/P	2.61**	0.04**	0.02	0.14**	3.69**	4.07**	0.030
	(96.28)	(2.95)	(1.54)	(2.76)	[0.04]	[0.01]	
LTG	2.47**	0.09**	0.01**	0.06**	12.70**	2.70*	0.038
	(55.87)	(4.38)	(2.15)	(6.97)	[< 0.01]	[0.05]	
Panel B: Individual Analysts' Accuracy Relative to Same Firm-Following Peers (N = 2,873)							
$\Delta Rec_{ij} = b_0 + b_1 \Delta V_{ij} + b_2(\Delta V_{ij} \times HiAcc_{ij}) + b_3(\Delta V_{ij} \times LoAcc_{ij}) + e_{ij}$							
V_{Fade}/P	−0.07	−0.17	0.16	−0.18	0.02	0.34	0.024
	(−1.44)	(−0.57)	(1.54)	(−0.59)	[0.90]	[0.50]	
V_{Perp}/P	−0.07	−0.01	0.02*	−0.01	1.46	0.25	0.011
	(−1.49)	(−0.85)	(1.94)	(−0.81)	[0.23]	[0.63]	
V_{LTG}/P	−0.08	−0.02**	0.02**	−0.02**	0.11	5.31**	0.058
	(−1.59)	(−2.52)	(2.51)	(−2.14)	[0.75]	[< 0.01]	
V_{PEG}/P	−0.08	0.05	0.07	0.02*	0.16	2.36*	0.034
	(−1.67)	(0.30)	(0.43)	(2.01)	[0.69]	[0.09]	
LTG	−0.07	0.01**	0.001	0.01**	1.53	2.47*	0.039
	(−1.48)	(2.11)	(1.90)	(2.48)	[0.22]	[0.06]	

Notes:
Rec is analyst *j*'s recommendation for firm *i;* the coding is inverted to get more meaningful coefficients, i.e., 5 (strong buy) to 1 (strong sell). We use four proxies for valuation (V_{ij}): we use the residual income model with a five-year horizon and the following terminal values mean-reverting towards the industry mean, V_{Fade}, a perpetuity V_{Perp}, and a growing perpetuity at the analyst's long-term growth rate, V_{LTG}. We also calculate two growth-based heuristics, V_{PEG}, which is two-year ahead forecasted earnings-per-share multiplied by LTG; and LTG, which is the analyst's forecast long-term earnings growth. *P* is price at the close on June 30. $HiAcc_{ij}$ is an indicator variable equal to 1 if the analyst is in the most accurate tercile based on both short-term and long-term forecast accuracy, and 0 otherwise; $LoAcc_{ij}$ is an indicator variable equal to 1 if the analyst is in the least accurate tercile based on both short-term and long-term forecast accuracy, and 0 otherwise. The *t*-statistics in parentheses control for clustered standard errors on two dimensions using firm and time (Petersen, 2009). This approach allows for correlations among analysts' forecasts in the same firm in the same year and different years. *F-test* refers to the *F*-statistic with the associated *p*-value reported in brackets below. ** and * indicate statistical significance at the 5% and 10% levels, respectively.

For example, the coefficient of the least accurate forecasters' interaction with LTG is 0.06 (t-statistic = 6.97). While the most accurate forecasters also have a significantly positive interaction with LTG ($b_3 = 0.01$; t-statistic = 2.15) it is significantly smaller than that of the least accurate forecasters with an F-statistic of 2.70. While we did not predict a positive interaction effect for the most accurate analysts and LTG, as our measure of accuracy includes accuracy on LTG, one possible explanation is that this positive association is due to the use of LTG in rigorous valuation models. Results are similar for the PEG ratio, except that the interaction term for the most accurate forecasters is not significantly different from zero. Taken together, these results provide some support for our hypothesis. Note that in this case, the magnitude of the accentuation of the bias is also economically significant for the least accurate forecasters.

(iii) Analysis of the Changes Model

Our results are based on a levels analysis and are subject to correlated omitted variable concerns. To address this concern, we take changes in both recommendations and valuation models and estimate the regression in equation (10) using these change variables in place of their levels. We present these results in Panel B of Table 3. Similar to Bradshaw (2004), we find that changes in recommendations are negatively associated with rigorous valuation models, but positively associated with changes in growth-based heuristics. As in Bradshaw (2004), many of the changes in the valuation models are not significantly associated with changes in recommendations on average.

Specifically, for the least accurate analysts, changes in recommendations are positively associated with changes in the PEG ratio, $b_3 = 0.02$ (t-statistic $= 2.01$) and with changes in the LTG, $b_3 = 0.01$ (t-statistic $= 2.48$). Although the positive association is not always significant, accuracy appears to mitigate the negative associations between changes in recommendations and changes in rigorous valuation models. In the V_{LTG} and V_{Perp} models, the bias appears to be mitigated completely for the accurate analysts group. However, we still find no evidence of a positive association between analyst accuracy and rigorous valuation models.

(iv) Further Tests of the Reputation-Building Hypotheses: Controlling for Long-Term Growth

As noted above, one possible explanation for our failure to find a positive association between recommendations and rigorous valuation models is that our accuracy measure includes long-term growth. Specifically, accurate forecasters may weight their growth expectations more heavily in their recommendations than we weight growth in our implementation of rigorous valuation models. To explore this issue further we estimate the following regression model:

$$Rec_{ij} = b_0 + b_1 V_{ij} + b_2 \mathrm{LTG}_{ij} + e_{ij} \tag{11}$$

where V_{ij} is the valuation estimate (V_{Fade}, V_{Perp}, V_{LTG}, V_{PEG}) to price ratio and LTG is long-term growth. We run this analysis separately for the most and least accurate analysts, as our goal is to compare the use of rigorous valuation models and PEG to the use of long-term growth within groups of analysts with similar incentives.

We report these results in Table 4. We find some evidence that, when we control for long-term growth, the recommendations of the most accurate analysts have a positive and significant association with rigorous valuation models. For example, in Panel A of Table 4, for the V_{Fade} specification, $b_1 = 0.05$ for the group of the most accurate analysts. We find similar results for V_{Perp}, V_{LTG}, and V_{PEG}. As expected, the coefficients on long-term growth are also generally positive for the accurate analysts group but are not statistically different from zero when the model includes V_{Fade}, V_{Perp}, or V_{LTG}. Our F-tests confirm that in this specification, the association between recommendations and rigorous valuation models is greater than the association with long-term growth.

Table 4

Forecast Accuracy and the Association Between Stock Recommendations and Fundamental to Price Ratios Controlling for Long-Term Growth

Valuation	b_0	b_1	b_2	*F-test* $b_1 = b_2$	*Adj.* R^2
Panel A: Most Accurate Analysts ($N = 1{,}900$)					
		$Rec_{ij} = b_0 + b_1 V_{ij} + b_2 LTG_{ij} + e_{ij}$			
V_{Fade}/P	2.50**	0.05*	0.02	3.12**	0.022
	(48.81)	(2.01)	(1.57)	[0.03]	
V_{Perp}/P	2.47**	0.04**	0.01	4.59**	0.012
	(48.53)	(2.59)	(1.25)	[0.01]	
V_{LTG}/P	2.48**	0.06**	0.01	4.01**	0.040
	(48.01)	(2.75)	(1.08)	[0.01]	
V_{PEG}/P	2.19**	0.03	0.02**	2.12*	0.033
	(48.81)	(1.89)	(2.02)	[0.09]	
Panel B: Least Accurate Analysts ($N = 2{,}262$)					
		$Rec_{ij} = b_0 + b_1 V_{ij} + b_2 LTG_{ij} + e_{ij}$			
V_{Fade}/P	2.48**	−0.15*	0.04**	6.51**	0.034
	(51.09)	(−1.97)	(3.58)	[< 0.01]	
V_{Perp}/P	2.47**	−0.07**	0.09**	6.27**	0.037
	(50.07)	(−2.82)	(3.56)	[< 0.01]	
V_{LTG}/P	2.50**	−0.10**	0.17**	9.33**	0.048
	(50.69)	(−2.69)	(3.53)	[< 0.01]	
V_{PEG}/P	2.19**	0.15**	0.10**	1.51	0.067
	(33.11)	(3.46)	(7.49)	[0.31]	

Notes:

Rec is analyst *j*'s recommendation for firm *i;* the coding is inverted to get more meaningful coefficients, i.e., 5 (strong buy) to 1 (strong sell). We use four proxies for valuation (V_{ij}): we use the residual income model with a five-year horizon and the following terminal values mean-reverting towards the industry mean, V_{Fade}, a perpetuity V_{Perp}, and a growing perpetuity at the analyst's long-term growth rate, V_{LTG}. We also calculate two growth-based heuristics, V_{PEG}, which is two-year ahead forecasted earnings-per-share multiplied by LTG; and LTG, which is the analyst's forecast long-term earnings growth. P is price at the close on June 30. $HiAcc_{ij}$ is an indicator variable equal to 1 if the analyst is in the most accurate tercile based on both short-term and long-term forecast accuracy, and 0 otherwise; $LoAcc_{ij}$ is an indicator variable equal to 1 if the analyst is in the least accurate tercile based on both short-term and long-term forecast accuracy, and 0 otherwise. The *t*-statistics in parentheses control for clustered standard errors on two dimensions using firm and time (Petersen, 2009). This approach allows for correlations among analysts' forecasts in the same firm in the same year and different years. *F-test* refers to the *F*-statistic associated with the test of the null hypothesis H_0: $b_2 = b_3$; the associated *p*-value is reported in brackets below. ** and * indicate statistical significance at the 5% and 10% levels, respectively.

In Panel B of Table 4 we report results for the least accurate analysts group. These results are generally consistent with our prior results, with evidence of a strong negative association with rigorous valuation models and a positive association with long-term growth.

(v) Analysis of Variation in Profitability of Analysts' Recommendations

In this section we investigate the profitability of recommendations of accurate and less accurate analysts conditional on the consistency between their recommendations and valuation models derived from their inputs. We estimate recommendation profitability for each individual analyst's recommendation as the market-adjusted buy-and-hold return to recommendation k made by analyst i for firm j. We compute the buy-and hold return (BHAR) for the recommended stock for the period starting from the day before the recommendation date until the earlier of 12 months after the return window starting date or two days before the next recommendation issued by the same analyst. We then subtract the buy-and-hold return of the value-weighted Center for Research in Security Prices (CRSP) index for the same period from the buy-and-hold return for the recommended stock.

For buy recommendations, we invest \$1 in the recommended stock; for hold and sell recommendations, we sell \$1 (Ertimur et al., 2007; and Gleason et al., 2009). We measure market-adjusted buy-and-hold returns as:

$$\mathrm{BHAR}_i = \left[\prod_{t=1}^{T} (1 + r_{it}) - \prod_{t=1}^{T} (1 + r_{m,t}) \right], \tag{12}$$

where r_{it} is the daily raw return for stock i and $r_{m,t}$ is the daily value-weighted return of the NYSE/AMEX/NASDAQ stocks over the same period.[19]

In Panel A of Table 5 , we report the means of future returns to portfolios formed on consistency between recommendations and each of the rigorous valuation models and long-term growth.[20] While the residual income model is implemented with error, we use a simple benchmark of the value-to-price ratio being above or below one to form these portfolios. Specifically, for this analysis, we consider a buy recommendation to be consistent with the valuation model if the value-to-price ratio is greater than one, and a sell recommendation to be consistent with the valuation model if the value-to-price ratio is less than one. We consider recommendations as inconsistent in the opposite cases. We present this analysis for the most and least accurate analysts separately.

Similar to Loh and Mian (2006), we find that the recommendations of the most accurate analysts appear to be profitable. We also find, however, that these returns appear profitable only when an analyst's recommendation is consistent with the recommendation based on the V/P ratio using the analyst's inputs. For example, in the V_{Perp} specification, buy recommendations from the most accurate analysts are profitable on average only in the stocks where V_{Perp}/P is above one, with a 6.74% return, while the return to the group of in the stocks where V_{Perp}/P is below one is not statistically different from zero. We find similar results for sell recommendations, with the group with sell recommendations and a V_{Perp}/P ratio below one having a significant negative return of −2.91%. When we examine returns to the least accurate analysts, we find that buy recommendations yield either negative or insignificant returns. Similarly, for the least accurate analysts we find evidence of a positive return to their sell recommendations.

In Panel B of Table 5, we supplement our portfolio analysis with regression analysis to further identify the sources of the association between recommendations and future returns. Specifically, in this section we use a multivariate design to consider the incremental effect of a recommendation's consistency with valuation models using the analysts' forecasts as inputs. We use interaction terms to capture the incremental

19 We find similar results when we compute a size decile adjusted BHAR (results available upon request from the authors). This is done by subtracting from the daily raw return for stock the daily return of the size decile to which the firm belongs in that year (Bradshaw, 2004).

20 Our sample size increases to 12,899 in this section as we include newly issued recommendations as well as recommendation revisions and reiterations. Results are qualitatively similar if we examine our sample of 6,732 observations that excludes revisions and reiterations.

Table 5

Relation Between Returns and Stock Recommendations, Valuation Estimates, and Accuracy

Panel A: Average Future Returns Constructed on the Basis of Recommendation and Valuation Model Consistency

	Consistent			Inconsistent		
	V/P > 1 Buy	*V/P < 1* Sell	*Buy-Sell Diff.*	*V/P < 1* Buy	*V/P > 1* Sell	*Buy-Sell Diff.*
Most accurate analysts						
V_{Fade}/P	7.41**	−3.21**	11.62**	−2.22	1.08	−3.30
V_{Perp}/P	6.74**	−2.91**	9.65**	−2.49	0.95	−3.44
V_{LTG}/P	7.01**	−3.68**	10.69**	−1.67	0.88	−2.55
V_{PEG}/P	3.21*	−2.51**	5.72*	−1.44	1.01	−2.45
LTG	1.55	−2.44*	3.99	0.66	−1.09	1.75
Least accurate analysts						
V_{Fade}/P	−4.86**	2.96*	−7.82*	−3.56	−1.77	−1.79
V_{Perp}/P	−3.69**	2.31*	−6.00*	−3.06	−3.95	0.90
V_{LTG}/P	−4.01*	1.39	−2.63	−2.66	−2.49	−0.17
V_{PEG}/P	0.91**	2.61	−1.70	−1.00	−3.01	2.01
LTG	0.95	−0.44	1.39	0.99	−0.49	1.48

Panel B: Multivariate Analysis of Future Returns

$$\mathrm{BHAR}_i = b_0 + b_1 V_{ij} + b_2 Buy_{ij} + b_3 Sell_{ij} + b_4 (V_{ij} + Buy_{ij}) + b_5 (V_{ij} \times Sell_{ij}) + e_i$$

Valuation	b_0	b_1	b_2	b_3	b_4	b_5	*Adj.* R^2
Most accurate analysts (N = 3,591)							
V_{Fade}/P	−0.32	0.26**	0.15	−0.14**	0.20**	−0.13**	0.070
	(−1.52)	(2.98)	(1.75)	(−2.12)	(2.32)	(−2.17)	
V_{Perp}/P	−0.28**	0.17**	0.08	−0.04*	0.18**	−0.07**	0.099
	(−2.63)	(2.61)	(1.28)	(−1.94)	(2.49)	(−2.28)	
V_{LTG}/P	−0.28**	0.14**	0.12	−0.01*	0.09**	−0.02**	0.167
	(−2.18)	(3.63)	(1.68)	(−1.94)	(2.96)	(−2.89)	
V_{PEG}/P	−0.33**	0.09**	0.09	0.00	0.02*	−0.07	0.098
	(−3.31)	(2.24)	(1.47)	(−1.01)	(2.00)	(−1.47)	
LTG	0.47	−0.02*	0.22	−0.02*	−0.08	−0.19**	0.033
	(1.45)	(−1.98)	(1.69)	(−1.98)	(−1.84)	(−2.45)	
Least accurate analysts (N = 4,865)							
V_{Fade}/P	−0.25**	−0.07	−0.30*	−0.14	−0.17	−0.18	0.035
	(−2.52)	(−0.93)	(−1.95)	(−1.12)	(−1.32)	(−1.77)	
V_{Perp}/P	−0.18**	−0.09	−0.08	−0.11	−0.07	−0.06	0.017
	(−3.03)	(−1.02)	(−1.87)	(−1.44)	(−1.23)	(−1.78)	
V_{LTG}/P	−0.09**	−0.14	−0.12	−0.13	−0.11	−0.06	0.008
	(−3.19)	(−1.23)	(−1.88)	(−1.84)	(−1.66)	(−1.87)	
V_{PEG}/P	−0.13**	−0.19*	−0.09	−0.20	−0.13*	−0.06	0.033
	(−4.01)	(−2.04)	(−1.55)	(−1.32)	(−2.02)	(−1.74)	
LTG	0.22**	−0.19**	−0.14	0.03**	−0.02**	0.19**	0.037
	(2.51)	(−3.17)	(−1.24)	(4.10)	(−2.73)	(3.57)	

Notes:

We compute the buy-and hold return (BHAR) for the recommended stock for the period starting from the day before the recommendation date until the earlier of 12 months after the return window starting date or two days before the next recommendation issued by the same analyst. We then subtract the buy-and-hold return of the value-weighted Center for Research in Security Prices (CRSP) index for the same period from the buy-and-hold return for the recommended stock. BHAR is converted into a dollar value return by multiplying by $1 for a buy and negative $1 for a sell. We use four proxies for valuation (V_{ij}): we use the residual income model with a five-year horizon and the following terminal values mean-reverting towards the industry mean, V_{Fade}, a perpetuity V_{Perp}, and a growing perpetuity at the analyst's long-term growth rate, V_{LTG}. We also calculate two growth-based heuristics, V_{PEG}, which is two-year ahead forecasted earnings-per-share multiplied by LTG; and LTG, which is the analyst's forecast long-term earnings growth. P is price at the close on June 30. The most (least) accurate analysts are those in the most (least) accurate tercile based on both short-term and long-term forecast accuracy. *Buy* (*Sell*) is an indicator variable equal to one if the outstanding recommendation of the analyst is a strong buy or buy (sell or underperform) recommendation and zero otherwise. The reported *t*-statistics are based on standard errors clustered by analyst to allow for multiple observations of the same analyst in the model. ** and * indicate statistical significance at the 5% and 10% levels, respectively.

investment performance of portfolios of interest; for example, the term $(V_{ij} \times Sell_{ij})$ indicates that a portfolio formed from sell recommendations is conditioned on the valuation estimate. In Panel B of Table 5 we report results from the following regression:

$$\mathrm{BHAR}_i = b_0 + b_1 V_{ij} + b_2 Buy_{ij} + b_3 Sell_{ij} + b_4 (V_{ij} + Buy_{ij}) + b_5 (V_{ij} \times Sell_{ij}) + e_i, \tag{13}$$

where V_{ij} is one of the four valuation estimates scaled by the closing price per share prior to the formation of BHAR_i,[21] or LTG, V_{ij} is included to control for the well-known positive association between rigorous valuation models and future returns and the well-known negative association between LTG and future returns (e.g., Frankel and Lee, 1998; and Bradshaw, 2004), Buy_{ij} is an indicator variable equal to one if the outstanding recommendation of analyst j for firm i is a strong buy or a buy recommendation and zero otherwise, and $Sell_{ij}$ is an indicator variable equal to one if the outstanding recommendation of analyst j for firm i is a sell or an underperform recommendation and zero otherwise. We report these regression estimates separately for the most and least accurate analysts and our five valuation models.

For the most accurate analysts, we find that the coefficients on V_{ij} are positive and significant for all models except LTG, which is consistent with prior research (Frankel and Lee, 1998; and Bradshaw, 2004). The positive coefficients on Buy_{ij} and the negative coefficients on $Sell_{ij}$ are often not statistically different from zero, which differs from the results of Loh and Mian (2006) who show that the recommendations of accurate analysts are profitable. This result is explained by the interaction terms in our model, which suggest that the recommendations of the most accurate forecasters are more profitable because of the consistency between their recommendations and valuation models. For example, in the V_{LTG} specification, the main effect of buy and sell recommendations are not significantly different from zero, while the interactions of buy and sell recommendations with the V_{LTG}/P ratio are significant at $b_4 = 0.09$ and $b_5 = -0.02$. Results are similar for the other rigorous valuation models and for PEG. Our results for LTG differ slightly in that only the consistency between LTG and sell recommendations is significant.

When we examine the sample of the least accurate analysts, we find results similar to those of the portfolio analysis above. The results for LTG are again counter-intuitive, with buy recommendations associated with negative returns and sell recommendations associated with positive returns. In addition, our results suggest that rigorous valuation models formed with the least accurate analysts' inputs are not associated with future returns. Taken together, our results help explain the difference in the profitability of the recommendations of the most and least accurate analysts documented in Loh and Mian (2006). Specifically, we find that the consistency between recommendations and valuation models helps explain the positive future returns from trading on the most accurate analysts' recommendations.

21 Following Brown and Pfeiffer (2008) we also scale by total assets per share and find qualitatively similar results.

5. ROBUSTNESS ANALYSIS

(i) Additional Analysis of All-Star Analysts

All-Star analysts are known to have more accurate earnings forecasts, and their forecasts have a greater effect on market prices (Stickel, 1992). In addition, Park and Stice (2000) find similar results for accurate analysts. In our context, All-Star status is a natural extension of the reputation-building effect through accuracy. Specifically, if the All-Star analysts have built their reputations through accurate forecasting, then we expect that reputation-building and All-Star analysts will similarly mitigate the use of overly optimistic valuation estimates in generating their recommendations.

In Table 6, we find evidence that partially supports our conjecture. Specifically, in Panel A, we find that the recommendations of All-Star analysts are similar to those of the most accurate analysts in their associations with rigorous valuation models and growth heuristics. We also find some evidence that, for the V_{LTG} and V_{Perp} models, All-Star analysts have a positive association with these rigorous valuation models (i.e., $b_1 + b_2 > 0$). In Panel B, All-Star analysts and accurate analysts are both significantly incrementally positively associated with rigorous valuation models and long-term growth (but again not with PEG). The F-tests, however, suggest that the differences between All-Star and high accuracy analysts are insignificant for all the valuation approaches except for V_{Fade}.

(ii) Robustness to Sample Selection

In Table 7, we provide additional robustness analysis for our sample selection criteria. Specifically, in Panel A, we broaden our sample to include firms with a following of fewer than three analysts. In this model, we rank the analyst's accuracy relative to all the peers within his or her industry, where industry is defined following the Fama and French (1997) 48-industry classification. For this sample, we also include the variance of the earnings-to-price ratio as a control for firm-specific factors:

$$Rec_{ij} - b_0 + b_1 V_{ij} + b_2(V_{ij} \times HiAcc_{ij}) + b_2(V_{ij} \times LoAcc_{ij}) + b_4 EVar_i + e_{ij}, \quad (11)$$

where V_{ij} is the valuation estimate (V_{Fade}, V_{Perp}, V_{LTG}, V_{PEG}) to price ratio or LTG; $HiAcc_{ij}$ is an indicator variable equal to 1 if the analyst is in the most accurate tercile based on both short- and long-term forecast accuracy, and 0 otherwise; $LoAcc_{ij}$ is an indicator variable equal to 1 if the analyst is in the least accurate tercile based on both short- and long-term forecast accuracy, and 0 otherwise; and $EVar_i$ is the coefficient of variation of the firm's earnings-to-price ratio included as a control for the firm-specific difficulty of forecasting future earnings in our industry group regressions (Wasley and Wu, 2006).

Our results for this larger sample of 9,765 are generally consistent with those of the smaller sample, although some of the results are stronger.[22] For example, in the V_{Perp} specification, the most accurate group of forecasters has a positive association between this rigorous valuation approach and recommendations. Specifically, the coefficient for the average analysts, b_1, is -0.04, and the interaction of $V_{ij} \times HiAcc_{ij}$ is 0.09. We

22 The sample size is larger because we added back the 8,343 analysts that have fewer than three distinct analysts following the stock (Table 1). Of the 26,310 firm-analyst observations, we delete 16,545 observations that are in the off-diagonal accuracy groupings, leaving us with 9,765 observations for this test.

Table 6

All-Star Analysts and the Association Between Stock Recommendations and Fundamental to Price Ratios

Panel A: All-Star Analysts Relative to Same Firm-Following Peers ($N = 6{,}732$)

$Rec_{ij} = b_0 + b_1 V_{ij} + b_2(V_{ij} \times AllStar_{ij}) + e_{ij}$

Valuation	b_0	b_1	b_2	*F-test* $b_1 + b_2 = 0$	*Adj.* R^2
V_{Fade}/P	2.67**	−0.10**	0.11**	0.05	0.024
	(297.83)	(−7.12)	(4.08)	[0.83]	
V_{Perp}/P	2.63**	−0.01	0.04**	4.00*	0.011
	(396.74)	(−1.20)	(2.88)	[0.05]	
V_{LTG}/P	2.64**	−0.04**	0.09**	5.24**	0.058
	(413.56)	(−6.12)	(2.64)	[0.02]	
V_{PEG}/P	2.61**	0.03**	0.06	3.10*	0.034
	(321.01)	(3.63)	(1.64)	[0.08]	
LTG	2.47**	0.09**	0.03**	11.68**	0.039
	(210.85)	(16.25)	(3.22)	[< 0.01]	

Panel B: All-Star versus Accurate Analysts Relative to Same Firm-Following Peers ($N = 6{,}732$)

$Rec_{ij} = b_0 + b_1 V_{ij} + b_2(V_{ij} \times AllStar_{ij}) + b_3(V_{ij} \times HiAcc_{ij}) + e_{ij}$

Valuation	b_0	b_1	b_2	b_3	*F-test* $b_2 = b_3$	*Adj.* R^2
V_{Fade}/P	2.67**	−0.10**	0.11**	0.07*	1.34	0.025
	(296.17)	(−6.91)	(4.07)	(1.93)	[0.11]	
V_{Perp}/P	2.63**	−0.05	0.04**	0.01**	1.25	0.020
	(396.66)	(−0.83)	(2.91)	(2.38)	[0.17]	
V_{LTG}/P	2.64**	−0.04**	0.02*	0.03**	0.99	0.059
	(413.56)	(−6.12)	(2.12)	(2.63)	[0.23]	
V_{PEG}/P	2.61**	0.03**	0.05	0.03	1.10	0.036
	(315.90)	(3.18)	(1.65)	(0.58)	[0.31]	
LTG	2.46**	0.09**	0.03**	0.02**	1.55	0.041
	(206.93)	(15.80)	(3.16)	(2.55)	[0.27]	

Notes:

Rec is analyst *j*'s recommendation for firm *i;* the coding is inverted to get more meaningful coefficients, i.e., 5 (strong buy) to 1 (strong sell). We use four proxies for valuation (V_{ij}): we use the residual income model with a five-year horizon and the following terminal values mean-reverting towards the industry mean, V_{Fade}, a perpetuity V_{Perp}, and a growing perpetuity at the analyst's long-term growth rate, V_{LTG}. We also calculate two growth-based heuristics, V_{PEG}, which is two-year ahead forecasted earnings-per-share multiplied by LTG; and LTG, which is the analyst's forecast long-term earnings growth. *P* is price at the close on June 30. $HiAcc_{ij}$ is an indicator variable equal to 1 if the analyst is in the most accurate tercile based on both short-term and long-term forecast accuracy, and 0 otherwise; $LoAcc_{ij}$ is an indicator variable equal to 1 if the analyst is in the least accurate tercile based on both short-term and long-term forecast accuracy, and 0 otherwise. *AllStar* is an indicator variable equal to 1 if analyst *j* is in the *Institutional Investor* All-American Research Team analysts, and 0 otherwise. The *t*-statistics in parentheses control for clustered standard errors on two dimensions using industry and time (Petersen, 2009). This approach allows for correlations among different industries in the same year and different years in the same industry. *F-test* refers to the *F*-statistic with the associated *p*-value reported in brackets below. ** and * indicate statistical significance at the 5% and 10% levels, respectively.

also find similar, but larger, differences in the magnitude for the PEG ratio; specifically, the least accurate group has a significant positive coefficient of 0.23, while the most accurate group has an insignificant coefficient.

In Panel B of Table 7, we broaden our main sample to include all analysts with available information, not just the analysts in the same accuracy group on both

Table 7

Robustness of Forecast Accuracy and the Association Between Stock Recommendations and Fundamental to Price Ratios to Broader Samples

Panel A: Individual Analysts Accuracy Relative to Industry Peers (N = 9,765)

$$Rec_{ij} - b_0 + b_1 V_{ij} + b_2(V_{ij} \times HiAcc_{ij}) + b_3(V_{ij} \times LoAcc_{ij}) + b_4 EVar_i + e_{ij}$$

Valuation	b_0	b_1	b_2	b_3	b_4	*F-test* $b_2 = b_3$	*Adj.* R^2
V_{Fade}/P	2.67**	−0.07**	0.04	−0.08**	−0.04**	11.47**	0.067
	(100.59)	(−2.57)	(1.41)	(−2.09)	(−2.75)	[< 0.001]	
V_{Perp}/P	2.64**	−0.04**	0.09**	−0.03**	−0.04**	11.6**	0.018
	(130.62)	(−2.35)	(2.35)	(−2.28)	(−2.51)	[< 0.001]	
V_{LTG}/P	2.64**	−0.02	0.03**	−0.03	−0.03**	9.37**	0.055
	(150.52)	(−1.75)	(2.61)	(−2.07)	(−2.24)	[< 0.001]	
V_{PEG}/P	2.62**	0.03**	0.06	0.23**	−0.03**	4.01**	0.029
	(108.86)	(2.28)	(1.13)	(2.14)	(−2.57)	[< 0.001]	
LTG	2.49**	0.08**	0.02**	0.04**	−0.03**	2.54**	0.051
	(53.18)	(3.22)	(2.10)	(5.35)	(−2.29)	[0.05]	

Panel B: Individual Analysts Accuracy Relative to Same Firm-Following Peers, Including Off-Diagonal Observations (N = 17,967)

$$Rec_{ij} - b_0 + b_1 V_{ij} + b_2(V_{ij} \times HiAcc_{ij}) + b_3(V_{ij} \times LoAcc_{ij}) + e_{ij}$$

Valuation	b_0	b_1	b_2	b_3	*F-test* $b_2 = b_3$	*Adj.* R^2
V_{Fade}/P	2.67**	−0.09**	0.02	−0.02**	7.07**	0.017
	(300.6)	(−3.31)	(0.88)	(−2.77)	[< 0.001]	
V_{Perp}/P	2.63**	0.01	0.01*	−0.01	9.02**	0.008
	(403.9)	(0.55)	(1.98)	(−1.65)	[< 0.001]	
V_{LTG}/P	2.64**	−0.04**	0.02	−0.01*	0.77	0.055
	(420.7)	(−5.09)	(1.64)	(−1.90)	[0.46]	
V_{PEG}/P	2.61**	0.03**	0.02	0.08**	7.99**	0.098
	(320.3)	(2.59)	(1.71)	(3.15)	[< 0.001]	
LTG	2.47**	0.01**	0.01	0.01**	4.55**	0.039
	(212.7)	(13.78)	(1.43)	(2.85)	[0.01]	

Notes:

Rec is analyst *j*'s recommendation for firm *i;* the coding is inverted to get more meaningful coefficients, i.e., 5 (strong buy) to 1 (strong sell). We use four proxies for valuation: V_{Fade} is a value estimate based on the residual income model with a five-year horizon and with post horizon residual income assumed to mean-revert towards the industry mean, V_{Perp} is a value estimate based on the residual income model (five-year horizon with perpetuity assumption), V_{LTG} is a value estimate based on the residual income model with a five-year horizon and with post horizon residual income assumed to grow at the analyst's long-term growth rate, and V_{PEG} is two-year ahead forecasted earnings-per-share multiplied by LTG. As a fifth measure we report LTG, which is the analyst's forecast long-term earnings growth. P is price at the close on June 30. $HiAcc_{ij}$ is an indicator variable equal to 1 if the analyst is in the most accurate tercile based on both short-term and long-term forecast accuracy, and 0 otherwise; $LoAcc_{ij}$ is an indicator variable equal to 1 if the analyst is in the least accurate tercile based on both short-term and long-term forecast accuracy, and 0 otherwise. *EVar* is the coefficient of variation of the firm's earnings-to-price ratio included as a control for the firm-specific difficulty to forecast future earnings in our industry group regressions. The t-statistics in parentheses control for clustered standard errors on two dimensions using (i) industry and time in Panel A and (ii) firm and time in Panel B (Petersen, 2009). *F-test* refers to the F-statistic associated with the test of the null hypothesis H_0: $b_2 = b_3$; the associated p-value is reported in brackets below. In Panel A we include firms with a following of fewer than three analysts and rank the analyst's accuracy relative to all the peers within their industry, where industry is defined following the Fama and French (1997) 48-industry classification. In Panel B we include all analyst-firm observations with at least three analysts following the stock with available information, not just the analysts in the same accuracy group on both short- and long-term dimensions (i.e., not just the diagonal observations). ** and * indicate statistical significance at the 5% and 10% levels, respectively.

short- and long-term dimensions. While the results are generally similar to our main results for the least accurate group and growth heuristics, we do find that our interactions for the most accurate groups with rigorous valuation models are weaker both in magnitude and statistical significance, consistent with the adding of noise to our measures of high and low accuracy.

6. CONCLUSION

We examine how individual analysts' incentives may affect the tendency of analysts to base their stock recommendations on growth-based heuristics instead of more rigorous valuation models. Our work is motivated by Bradshaw's (2004) finding that analysts, as a group, tend to align their recommendations with growth-based heuristics. Prior literature has also shown that this effect is mitigated by recent regulation (Barniv et al., 2009a; and Chen and Chen, 2009) and for analysts belonging to more independent investment banking firms (Ertimur et al., 2007). We contribute to this literature by examining whether variation in individual analysts' trade-generating incentives affects how they appear to use the information in various valuation models in generating their recommendations.

We examine the role of reputation building, which we measure as the analyst's relative forecast accuracy following Jackson (2005). We find that the recommendations of the most accurate forecasters for each firm have a significantly lower correlation with growth-based heuristics than those of their less accurate peers. To the extent that growth-based heuristics are optimistic and not good predictors of future returns, these results are consistent with reputation incentives countering the incentive to be optimistic. We find that the negative association documented in Bradshaw (2004) between recommendations and rigorous valuation models is concentrated in the least accurate analysts. We also find some support for a positive association between the recommendations of accurate and rigorous valuation models when controlling for long-term growth.

We find an economically meaningful difference in the profitability of the recommendations of the most and least accurate analysts, due to the differences in the consistency between their recommendations and valuation models constructed using their forecasts as inputs. Specifically, the buy and sell recommendations that are consistent with rigorous valuation models appear profitable for the most accurate analysts, but appear unprofitable for the least accurate analysts.

Our results are not explained by variation in the firm-specific difficulty of forecasting future earnings and are generally robust to potentially confounding omitted variables when we use a changes analysis. Consistent with reputation building, the recommendations of All-Star analysts and accurate forecasters have similar associations with both rigorous and heuristic valuation approaches, and we find some evidence that All-Star analysts have a positive association with rigorous valuation models.

Overall, our results help to reconcile the differing conclusions in prior literature surrounding the usefulness of analysts' stock recommendations. Consistent with prior research, our results suggest that, on average, there is a strong bias towards recommending stocks based on growth-based heuristics. We find, however, that this bias is strongest for the least accurate analysts and weakest for the most accurate analysts. As we find only modest evidence of a positive association between recommendations and rigorous valuation models, even for the most accurate analysts and All-Stars, future research could consider alternative sources of information that would help explain why the recommendations of accurate analysts are associated with future returns. One possibility is that analysts may have insights on managerial ability.

REFERENCES

Asquith, P., M. B. Mikhail and A. S. Au (2005), 'Information Content of Equity Analyst Reports', *Journal of Financial Economics*, Vol. 75, No. 2, pp. 245–82.

Barker, R. (1999), 'The Use of Dividends in Valuation Models used by Analysts and Fund Managers', *European Accounting Review*, Vol. 8, No. 2, pp. 195–218.

Barniv, R., O.-K. Hope, M. Myring and W. B. Thomas (2009a), 'Do Analysts Practice What They Preach and Should Investors Listen? Effects of Recent Regulation', *The Accounting Review*, Vol. 84, No. 4, pp. 1015–39.

——— ——— ——— ——— (2009b), 'International Evidence on Analyst Stock Recommendations, Valuations, and Returns', Working Paper (Kent State University, University of Toronto, Ball State University, and University of Oklahoma).

Block, S. B. (1999), 'A Study of Financial Analysts: Practice and Theory', *Financial Analysts Journal*, Vol. 55, No. 4, pp. 86–95.

Bradley, D. J., J. Clarke and J. Cooney Jr. (2009), 'Does Reputation Mitigate Analysts' Conflicts of Interest? Evidence from Recommendations', Working Paper (University of South Florida).

Bradshaw, M. T. (2002), 'The Use of Target Prices to Justify Sell-Side Analysts' Stock Recommendations', *Accounting Horizons*, Vol. 16, No. 1, pp. 27–41.

——— (2004), 'How Do Analysts Use Their Earnings Forecasts in Generating Stock Recommendations?' *Accounting Review*, Vol. 79, No. 1, pp. 25–50.

——— (2010), 'Analysts' Forecasts: What Do We Know After Decades of Work?' Working Paper (Boston College).

——— and R. G. Sloan (2002), 'GAAP versus The Street: An Empirical Assessment of Two Alternative Definitions of Earnings', *Journal of Accounting Research*, Vol. 40, No. 1, pp. 41–66.

———, S. A. Richardson and R. G. Sloan (2006), 'The Relation Between Corporate Financing Decisions, Analysts' Forecasts and Stock Returns,' *Journal of Accounting and Economics*, Vol. 42, No. 1-2, pp. 53–85.

Breton, G. and R. Taffler (2001), 'Accounting Information and Analyst Stock Recommendation Decisions: A Content Analysis Approach', *Accounting and Business Research*, Vol. 31, No. 2, pp. 91–101.

Brown, L. D. (1993), 'Earnings Forecasting Research: Its Implications for Capital Markets Research', *International Journal of Forecasting*, Vol. 9, No. 3, pp. 295–320.

——— and K. Huang, (2010), 'Forecast-Recommendation Consistency and Earnings Forecast Quality', Working Paper (Georgia State University).

Brown, W. D. and R. J. Pfeiffer Jr. (2008), 'Do Investors Under-React to Information in Analysts' Earnings Forecasts?' *Journal of Business Finance & Accounting*, Vol. 35, Nos. 7&8, pp. 889–911.

Chen, C.-Y. and P. F. Chen (2009), 'NASD Rule 2711 and Changes in Analysts' Independence in Making Stock Recommendations', *The Accounting Review*, Vol. 84, No. 4, pp. 1041–71.

Cowen, A., B. Groysberg and P. Healy (2006), 'Which Types of Analysts Firms are More Optimistic?' *Journal of Accounting and Economics*, Vol. 41, No. 1, pp. 119–146.

Dechow, P. M., A. P. Hutton and R. G. Sloan (2000), 'The Relation Between Analysts' Forecasts of Long-Term Earnings Growth and Stock Price Performance Following Equity Offerings', *Contemporary Accounting Research*, Vol. 17, No. 1, pp. 1–34.

Deloof, M., W. De Maeseneire and K. Inghelbrecht (2009), 'How do Investment Banks Value Initial Public Offerings (IPOs)?' *Journal of Business Finance & Accounting*, Vol. 36, Nos. 1&2, pp. 130–60.

Demirakos, E. G., N. C. Strong and M. Walker (2004), 'What Valuation Models Do Analysts Use?' *Accounting Horizons*, Vol. 18, No. 4, pp. 221–40.

——— ——— ——— (2009), 'Does Valuation Accuracy Affect Target Price Accuracy?' *European Accounting Review*, Vol. 19, No. 1, pp. 35–72.

Ertimur, Y., J. Sunder and S. Sunder (2007), 'Measure for Measure: An Examination of the Association Between Forecast Accuracy and Recommendation Profitability of Sell-Side Analysts', *Journal of Accounting Research*, Vol. 45, No. 3, pp. 567–606.

Ertimur, Y., V. Muslu and F. Zhang,(2008), 'The Long-Run Performance of Analyst Coverage Initiations', Working Paper (Duke University).

Fama, E. F. and K. R. French (1997), 'Industry Costs of Equity', *Journal of Financial Economics*, Vol. 43, No. 2, pp. 153–93.

Finger, C. A. and W. R. Landsman,(1998), 'What Do Analysts' Stock Recommendations Really Mean?' Working Paper (University of Illinois and U.N.C. – Chapel Hill).

Frankel, R. and C. M. C. Lee (1998), 'Accounting Valuation, Market Expectation, and Cross-Sectional Stock Returns', *Journal of Accounting and Economics*, Vol. 25, No. 3, pp. 283–319.

Glaum M. and N. Friedrich (2006), 'After the Bubble: Valuation of Telecommunications Companies by Financial Analysts', *Journal of International Financial Management & Accounting*, Vol. 17, No. 2, pp. 1607–174.

Gleason, C. A., B. Johnson and H. Li (2009), 'The Earnings Forecast Accuracy, Valuation Model Use, and Price Target Performance of Sell-Side Equity Analysts', Working Paper (University of Iowa).

Groysberg, B., P. M. Healy and D. Maber,(2008), 'What Drives Sell-Side Analyst Compensation at High-Status Banks?' Working Paper (Harvard Business School).

Harris, R. D. F. (1999), 'The Accuracy, Bias and Efficiency of Analysts' Long Run Earnings Growth Forecasts', *Journal of Business Finance & Accounting*, Vol. 26, Nos. 5&6, pp. 725–55.

Hayes, R. M. (1998), 'The Impact of Trading Commission Incentives on Analysts' Stock Coverage Decisions and Earnings Forecasts', *Journal of Accounting Research*, Vol. 36, No. 2, pp. 299–320.

Hong, H. and J. D. Kubik (2003), 'Analyzing the Analysts: Career Concerns and Biased Earnings Forecasts', *Journal of Finance*, Vol. 58, No. 1, pp. 313–51.

——— ——— and A. Solomon (2000), 'Security Analysts' Career Concerns and Herding of Earnings Forecasts', *RAND Journal of Economics*, Vol. 31, No. 1, pp. 121–44.

Imam, S., R. Barker and C. Clubb (2008), 'The Use of Valuation Models by UK Investment Analysts', *The European Accounting Review*, Vol. 17, No. 3, pp. 503–35.

Irvine, P. J. A. (2001), 'Do Analysts Generate Trade for Their Firms? Evidence from the Toronto Stock Exchange', *Journal of Accounting and Economics*, Vol. 30, No. 2, pp. 209–26.

Jackson, A. R.,(2005), 'Trade Generation, Reputation, and Sell-Side Analysts', *Journal of Finance*, Vol. 60, No. 2, pp. 673–717.

Jegadeesh, N., J. Kim, S. D. Krische and C. M. C. Lee (2004), 'Analyzing the Analysts: When Do Recommendations Add Value?' *Journal of Finance*, Vol. 59, No. 3, pp. 1083–124.

Ke, B. and Y. Yu (2009), 'Why Don't Analysts Use Their Earnings Forecasts in Generating Stock Recommendations?' Working Paper (Pennsylvania State University).

Kecskes, A., R. Michaely and K. Womack (2010), 'What Drives the Value of Analysts' Recommendations: Earnings Estimates or Discount Rate Estimates?' Working Paper (Virginia Polytechnic State University, Cornell University, and University of Toronto).

La Porta, R. (1996), 'Expectations and the Cross-Section of Stock Returns', *Journal of Finance*, Vol. 51, No. 5, pp. 1715–42.

Lee, C. M. C., J. Myers and B. Swaminathan (1999), 'What is the Intrinsic Value of the Dow?' *Journal of Finance*, Vol. 54, No. 5, pp. 1693–741.

Loh, R. K. and G. M. Mian (2006), 'Do Accurate Earnings Forecasts Facilitate Superior Investment Recommendations?' *Journal of Financial Economics*, Vol. 80, No. 2, pp. 455–83.

Lundholm, R. and T. O'Keefe (2001), 'Reconciling Value Estimates from the Discounted Cash Flow Model and the Residual Income Model', *Contemporary Accounting Research*, Vol. 18, No. 2, pp. 311–35.

——— and R. Sloan (2007), *Equity Valuation and Analysis with eVal*, 2nd Edition (Boston: McGraw Hill).

Mikhail, M. B., B. R. Walther, and R. H. Willis (1999), 'Does Forecast Accuracy Matter to Security Analysts?' *The Accounting Review*, Vol. 74, No. 2, pp. 185–200.

Mokoaleli-Mokotelli, T., R. J. Taffler and V. Agarwal (2009), 'Behavioural Bias and Conflicts of Interest in Analyst Stock Recommendations', *Journal of Business Finance & Accounting*, Vol. 36, Nos. 3&4, pp. 384–418.

Ohlson, J. A. (1995), 'Earnings, Book Values, and Dividends in Equity Valuation', *Contemporary Accounting Research*, Vol. 11, No. 2, pp.661–76.

Park, C. W. and E. K. Stice (2000), 'Analyst Forecasting Ability and the Stock Price Reaction to Forecast Revisions', *Review of Accounting Studies*, Vol. 5, No. 3, pp. 259–72.

Penman, S. H. (2001), 'On Comparing Cash Flow and Accrual Accounting Models for Use in Equity Valuation: A Response to Lundholm and O'Keefe', *Contemporary Accounting Research*, Vol. 18, No. 4, pp. 681–92.

Petersen, M. A. (2009), 'Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches', *Review of Financial Studies*, Vol. 22, No. 1, pp. 435–80.

Rountree, B. R. (2009), 'Discussion of Behavioural Bias and Conflicts of Interest in Analyst Stock Recommendations', *Journal of Business Finance & Accounting*, Vol. 36, Nos. 3&4, pp. 419–23.

Schipper, K. (1991), 'Analysts' Forecasts', *Accounting Horizons*, Vol. 5, No. 4, pp. 105–21.

Sinha, P., L. D. Brown and S. Das (1997), 'A Re-Examination of Financial Analysts' Differential Earnings Forecast Accuracy', *Contemporary Accounting Research*, Vol. 14, No. 1, pp. 1–42.

Stickel, S. E. (1992), 'Reputation and Performance among Security Analysts', *Journal of Finance*, Vol. 47, No. 5, pp. 1811–36.

——— (1995), 'The Anatomy of the Performance of Buy and Sell Recommendations', *Financial Analysts Journal*, Vol. 51, pp. 25–39.

Wasley, C. E. and J. S. Wu (2006), 'Why Do Managers Voluntarily Issue Cash Flow Forecasts?' *Journal of Accounting Research*, Vol. 44, No. 2, pp. 389–429.