



Advances in Business and Management Forecasting

Emerald Book Chapter: An Evaluation of Financial Analysts and Naïve Methods in Forecasting Long-Term Earnings

Michael Lacina, B. Brian Lee, Randall Zhaohui Xu

Article information:

To cite this document:

Michael Lacina, B. Brian Lee, Randall Zhaohui Xu, (2011), "An Evaluation of Financial Analysts and Naïve Methods in Forecasting Long-Term Earnings", Kenneth D. Lawrence, Ronald K. Klimberg, in (ed.) *Advances in Business and Management Forecasting (Advances in Business and Management Forecasting, Volume 8)*, Emerald Group Publishing Limited, pp. 77 - 101

Permanent link to this document:

[http://dx.doi.org/10.1108/S1477-4070\(2011\)0000008009](http://dx.doi.org/10.1108/S1477-4070(2011)0000008009)

Downloaded on: 01-06-2012

References: This document contains references to 39 other documents

To copy this document: permissions@emeraldinsight.com

This document has been downloaded 181 times since 2011. *

Users who downloaded this Chapter also downloaded: *

Gary Kleinman, Dinesh Pai, Kenneth D. Lawrence, (2011), "Short-Term Predictions of the Total Medical Costs of California Counties", Kenneth D. Lawrence, Ronald K. Klimberg, in (ed.) *Advances in Business and Management Forecasting (Advances in Business and Management Forecasting, Volume 8)*, Emerald Group Publishing Limited, pp. 105 - 113

[http://dx.doi.org/10.1108/S1477-4070\(2011\)0000008010](http://dx.doi.org/10.1108/S1477-4070(2011)0000008010)

Amitava Mitra, Jayprakash G. Patankar, (2011), "A Multiobjective Model for Warranty Policies Integrating Product Quality, Market Share, and R&D Expenditures", Kenneth D. Lawrence, Ronald K. Klimberg, in (ed.) *Advances in Business and Management Forecasting (Advances in Business and Management Forecasting, Volume 8)*, Emerald Group Publishing Limited, pp. 43 - 65

[http://dx.doi.org/10.1108/S1477-4070\(2011\)0000008007](http://dx.doi.org/10.1108/S1477-4070(2011)0000008007)

Rung-Chuan Lin, Kalyan S. Pasupathy, Mustafa Y. Sir, (2011), "Estimating Admissions and Discharges for Planning Purposes - Case of an Academic Health System", Kenneth D. Lawrence, Ronald K. Klimberg, in (ed.) *Advances in Business and Management Forecasting (Advances in Business and Management Forecasting, Volume 8)*, Emerald Group Publishing Limited, pp. 115 - 128

[http://dx.doi.org/10.1108/S1477-4070\(2011\)0000008011](http://dx.doi.org/10.1108/S1477-4070(2011)0000008011)

Access to this document was granted through an Emerald subscription provided by PENNSYLVANIA STATE UNIVERSITY

For Authors:

If you would like to write for this, or any other Emerald publication, then please use our Emerald for Authors service.

Information about how to choose which publication to write for and submission guidelines are available for all. Additional help for authors is available for Emerald subscribers. Please visit www.emeraldinsight.com/authors for more information.

About Emerald www.emeraldinsight.com

With over forty years' experience, Emerald Group Publishing is a leading independent publisher of global research with impact in business, society, public policy and education. In total, Emerald publishes over 275 journals and more than 130 book series, as well as an extensive range of online products and services. Emerald is both COUNTER 3 and TRANSFER compliant. The organization is a partner of the Committee on Publication Ethics (COPE) and also works with Portico and the LOCKSS initiative for digital archive preservation.

*Related content and download information correct at time of download.

AN EVALUATION OF FINANCIAL ANALYSTS AND NAÏVE METHODS IN FORECASTING LONG-TERM EARNINGS

Michael Lacina, B. Brian Lee and Randall
Zhaohui Xu

ABSTRACT

We evaluate the performance of financial analysts versus naïve models in making long-term earnings forecasts. Long-term earnings forecasts are generally defined as third-, fourth-, and fifth-year earnings forecasts. We find that for the fourth and fifth years, analysts' forecasts are no more accurate than naïve random walk (RW) forecasts or naïve RW with economic growth forecasts. Furthermore, naïve model forecasts contain a large amount of incremental information over analysts' long-term forecasts in explaining future actual earnings. Tests based on subsamples show that the performance of analysts' long-term forecasts declines relative to naïve model forecasts for firms with high past earnings growth and low analyst coverage. Furthermore, a model that combines a naïve benchmark (last year's earnings) with the analyst long-term earnings growth forecast does not perform better than analysts' forecasts or naïve model forecasts. Our findings suggest that analysts' long-term earnings

Advances in Business and Management Forecasting, Volume 8, 77–101

Copyright © 2011 by Emerald Group Publishing Limited

All rights of reproduction in any form reserved

ISSN: 1477-4070/doi:10.1108/S1477-4070(2011)000008009

forecasts should be used with caution by researchers and practitioners. Also, when analysts' earnings forecasts are unavailable, naïve model earnings forecasts may be sufficient for measuring long-term earnings expectations.

INTRODUCTION

This chapter evaluates the performance of financial analysts versus naïve models in forecasting long-term earnings. Analysts' earnings forecasts are widely used in accounting research as proxy for market expected earnings (Ramnath, Rock, & Shane, 2008; Schipper, 1991). The underlying assumption is that in an informationally efficient market, the capital market should use the best future earnings data available, where the best is defined as the most accurate (Brown, 1993). Indeed, many researchers in recent years have assumed that analysts' forecasts are superior to those of naïve and time series models.¹ However, prior evidence on the superiority of analysts' earnings forecasts over statistical model forecasts mainly originates from studies that focus on a comparison of predictive accuracy for short-term earnings forecasts, typically for the upcoming quarters or the coming year (e.g., Brown, Griffin, Hagerman, & Zmijewski, 1987a, 1987b; Brown, Richardson, & Schwager, 1987; Brown & Rozeff, 1978; Fried & Givoly, 1982; Imhoff & Pare, 1982).

Analysts tend to have a timing advantage over naïve and time series models in predicting short-term earnings due to the information available between the end of the final time period included in the forecast model and the date the analyst makes a forecast. Analysts do not have as much of a timing advantage over naïve and time series methods in making earnings forecasts over longer horizons, which normally extend more than two years from the forecast date. Furthermore, analysts are often evaluated on the accuracy of their short-term forecasts but not of their long-term forecasts (Dechow, Hutton, & Sloan, 2000; Stickel, 1992). This would on average provide analysts with more of an incentive to be accurate in their short-term forecasts than in their long-term forecasts. In fact, Chan, Karceski, and Lakonishok (2003) find that analysts' long-term earnings growth forecasts are overly optimistic and have little predictive power. The questionable predictive ability of analysts' long-term growth forecasts puts doubt on the assumption that analysts' forecasts are the default proxy for market expectations of long-term earnings extending beyond two years. Nevertheless,

long-term earnings growth forecasts are widely disseminated by financial analysts. Bradshaw (2004) finds that analysts use their long-term earnings growth forecasts in formulating stock recommendations. Moreover, prior studies plug in up to five years of analysts' earnings forecasts into earnings-based valuation models to infer the implied cost of capital (e.g., Botosan & Plumlee, 2005; Claus & Thomas, 2001; P. Easton, Taylor, Shroff, & Sougiannis, 2002) or assess firms' intrinsic values (e.g., Frankel & Lee, 1998; Sougiannis & Yaekura, 2001).

When earnings forecasts serve as inputs to valuation models, the accuracy of the earnings forecasts directly affects the estimates of cost of capital and intrinsic values. For example, P. Easton and Sommers (2007) find that optimism in analysts' earnings forecasts leads to an upward bias in the estimated cost of capital of about 3%. P. Easton and Monahan (2005) show that cost of capital derived from analysts' earnings forecasts is negatively correlated with realized returns after controlling for proxies for cash flow news and discount rate news. Similarly, prior studies (e.g., Francis, Olsson, & Oswald, 2000; Sougiannis & Yaekura, 2001) find large valuation errors from valuation models that use analysts' forecasts as a proxy for future earnings. Evidence in P. Easton and Monahan (2005) and Sougiannis and Yaekura (2001) suggests that their aforementioned findings are partially due to problems with analyst earnings forecast quality. Therefore, it is important to examine the performance of analysts' forecasts against alternative sources of earnings forecasts such as statistical models. The findings will provide fresh insight into the appropriateness of using analysts' forecasts as the default proxy for expected earnings in academic research.

A number of studies that examine the performance of analysts' long-term earnings forecasts use samples selected based on a transaction that has taken place, which limits the generalizability of their findings.² There are exceptions, that is, Cragg and Malkiel (1968) and Rozeff (1983). Cragg and Malkiel (1968) find that analysts' long-term earnings growth forecasts are on the whole no more accurate than naïve forecasts based on past earnings growth. They use analysts' forecasts made in 1962 and 1963 by five brokerage houses for 185 firms. On the contrary, Rozeff (1983) finds that growth rates derived from four- to five-year earnings forecasts from *Value Line* are more accurate than the corresponding growth rates implicit in four expected stock return models. His study uses a sample that includes *Value Line* long-term earnings forecasts made in 1967 (253 firms) and 1972 (348 firms). Given the poor performance of analysts' long-term earnings growth forecasts found in Chan et al.(2003) and the small samples from the 1960s and early 1970s used in Cragg and Malkiel (1968) and Rozeff (1983), it is

important to reexamine the performance of analysts' long-term earnings forecasts versus those of naïve models.

We use *I/B/E/S* analyst forecast data to compare analysts' long-term earnings forecasts with those of two naïve models. Whereas the analysts' first year (end of year following last reported annual earnings) and second year earnings forecasts are normally considered short-term forecasts, the third year through fifth-year forecasts are generally considered long term. Analysts' long-term earnings forecasts are either obtained directly on *I/B/E/S* or derived using the analysts' last available explicit earnings forecast with the analysts' long-term earnings growth rate, as is often done in the literature.³ The two naïve earnings forecast models are a random walk (RW) model and a RW with a drift based on historical inflation and historical real GDP growth (RWGDP).⁴ Additionally, some researchers have found that combining analysts' forecasts with naïve benchmarks can improve forecast accuracy (e.g., Cheng, Fan, & So, 2003; Conroy & Harris, 1987; Newbold, Zumwalt, & Kannan, 1987). Therefore, we also examine whether a hybrid model (RWLTG) combining a naïve benchmark, last year's earnings, with the analysts' long-term earnings growth rate forecast can improve long-term earnings forecast accuracy. The performances of the analyst, naïve, and hybrid forecasts are evaluated by examining their accuracy and information content.

The results for short-term forecast horizons show that analysts' earnings forecasts are more accurate than RW and RWGDP forecasts, which is consistent with prior research. However, as the forecast horizon extends beyond the second year, the higher accuracy of analysts' forecasts wanes such that for long-term horizons (especially fourth and fifth years), we cannot conclude whether analysts' forecasts are more accurate than RW or RWGDP forecasts. In some cases, we find evidence that the RWGDP model is more accurate than analysts' forecasts. As far as information content is concerned, a regression analysis shows that analysts' forecasts provide the majority of the information in explaining first- and second-year actual earnings. However, naïve model forecasts provide substantial incremental information over analysts' forecasts in explaining future actual earnings as the forecast horizon is extended beyond the second year.

We perform additional tests of accuracy and information content. First, we run the analyses on sample partitions. The results of these tests show that the performance of analysts' earnings forecasts declines relative to naïve model forecasts for firms with high past earnings growth and low analyst following. Also, when analysts issue explicit (as opposed to growth rate) long-term earnings forecasts, the performance of their forecasts improves relative to naïve model forecasts for only the fifth year in the forecast

horizon. However, financial analysts infrequently issue explicit earnings forecasts for the fifth year. Second, we compare earnings forecasts of the hybrid RWLTG model with analysts' forecasts and RWGDP forecasts (the most accurate naïve forecast). We find that the hybrid RWLTG model does not enhance forecast accuracy. Furthermore, the hybrid model forecasts contain less information content in explaining future earnings than RWGDP model forecasts or analysts' forecasts.

Our results convey that academics and practitioners should use analysts' long-term earnings forecasts with caution, especially for firms with high earnings growth. These analyst long-term forecasts appear to be no more accurate than some of the simple, naïve forecasts. Also, much of the information useful in explaining long-term future actual earnings is provided by naïve forecasts as opposed to analysts' forecasts. Our findings imply that the use of naïve forecast models such as RWGDP and RW may be sufficient and easily derived ways of forecasting long-term earnings when analysts' forecasts are unavailable. It is well known that analyst coverage is affected by various factors, and analysts tend to cover firms that are large and profitable (Bhushan, 1989; Hong, Lim, & Stein, 2000). Therefore, using forecasts from naïve models enables researchers to expand the sample to include firms without analyst coverage, thereby reducing the potential sampling bias in research design that limits the generalizability of their findings. This study contributes to the burgeoning stream of research that uses alternative earnings forecasts as a proxy for expected earnings. For example, Allee (2009) and Hou, van Dijk, and Zhang (2010) use earnings forecasts derived from time series models and a cross-sectional model, respectively, to estimate cost of capital.

The chapter proceeds as follows. The second section reviews relevant literature. In the third section, we explain the chapter's methodology. The fourth section discusses the results, including those for the full sample, sample partitions, and the hybrid model. The fifth section contains the conclusions.

LITERATURE REVIEW

Much of the literature that compares analysts' earnings forecasts with naïve or time series forecasts focuses on short-term forecasts. Brown and Rozeff (1978) examine quarterly earnings forecasts ranging from one quarter to five quarters ahead and first (current)-year annual earnings forecasts. They find that *Value Line* analysts' forecasts, on the whole, are more accurate than time series forecasts. Imhoff and Pare (1982) show that analysts' forecasts on

average outperform time series forecasts in terms of accuracy when the forecast horizon is four quarters ahead but not when it is three quarters ahead. [Fried and Givoly \(1982\)](#) examine first-year annual earnings forecasts and find that analysts' forecasts are more accurate than forecasts from two time series models. [Brown et al. \(1987\)](#) test analysts' one, two, and three-quarter-ahead forecasts from *Value Line* made one, two, and three months before the end of a quarter and analysts' first- and second-year annual forecasts from *I/B/E/S*. Their findings support the superiority of analysts' forecasts over time series forecasts. [Cheng et al. \(2003\)](#) use *I/B/E/S* analysts' first-year annual forecasts from Hong Kong. For the first 10 months following the previous earnings announcement, both analysts and RW forecasts have information content in explaining actual earnings. However, analysts' forecasts have relatively more information content as the earnings announcement date approaches. [Brown et al. \(1987a\)](#) test quarterly forecasts from one to three quarters ahead and find that the predictive accuracy of analysts' forecasts is superior to that of time series forecasts. They attribute this analyst superiority to two factors: (1) a contemporaneous advantage due to an analyst's ability to make better use of current information and (2) a timing advantage stemming from the acquisition of information by an analyst between the date the naïve forecast is made and the date the analyst forecast is made. However, although timing can be a major advantage for analysts relative to naïve methods for short-term forecasts, this advantage is less likely to have a significant impact on long-term forecasts.

Research that directly examines the performance of analysts' long-term forecasts has been sparse. [Cragg and Malkiel \(1968\)](#) study the accuracy of analysts' five-year earnings growth forecasts from five brokerage houses. They find that analysts' five-year earnings growth forecasts are no more accurate than long-term earnings growth forecasts based on past earnings growth rates or price-to-earnings ratios. On the contrary, analysts' five-year growth forecasts are found to be more accurate than naïve forecasts of no earnings growth. [Rozeff \(1983\)](#) uses four-to-five year earnings growth rates from *Value Line* analysts during 1967 and 1972. These forecasts are found to predict long-term earnings growth better than naïve forecasts from four expected return models. [Chan et al. \(2003\)](#) analyze the growth rates of earnings and sales. They document that analysts' long-term earnings growth forecasts are overly optimistic and have little predictive power for future earnings. A defect of these forecasts is that analysts predict sustained earnings growth rates over a long future time horizon (e.g., three to five years) for a large proportion of firms. On the contrary, the authors show that only 12.2% (2.6%) of their sample firms achieve above median growth in income

before extraordinary items for three (five) straight years. Dechow et al. (2000) study analysts' long-term earnings growth forecasts made around the equity offerings and find that the forecasts are systematically optimistic. Bradshaw (2004) documents that analysts use their long-term earnings growth forecasts in generating stock recommendations but that their long-term earnings growth forecasts are *negatively* related to future returns.

METHODOLOGY

Sample Selection

Our sample is from the *I/B/E/S* database. For the month of June for each year from 1988 to 2003, we obtain the median consensus analysts' earnings forecasts for up to five years ahead and the median consensus analysts' forecasted long-term earnings growth rate.⁵ *I/B/E/S* recommends the usage of the median (as opposed to mean) long-term earnings growth rate forecast to prevent excessive influence from outliers (Thomson Financial, 2004). We retrieve actual earnings per share (EPS) from *I/B/E/S* through 2007. To allow comparison using similar samples across forecast horizons, we require each firm year to have actual EPS for the upcoming five years.⁶ Stock price, which is used as a deflator in some of the analyses, is acquired from the *CRSP* database. We keep only firm years with December fiscal year ends to align the time horizons for analysts' earnings forecasts in our sample. The analysts' earnings forecasts and the actual earnings, which are in per share format, are adjusted for stock dividends and stock splits to coincide with the number of shares outstanding as of the June base month. Furthermore, analysts' forecasts in fully diluted form are adjusted to the basic format. If, for some reason, the firm has yet to release its prior year earnings before the *I/B/E/S* June consensus earnings forecast period, we drop the observation. Our final sample contains 27,081 firm years. There are fewer firm years in the individual analyses due to missing forecasts from analysts and naïve models, missing actual EPS, or missing stock price when applicable.

Analyst and Model Forecasts

The first-year analysts' earnings forecasts are obtained from *I/B/E/S* and designated as year t (first-year) forecasts. For the subsequent four years, year $t + 1$ through year $t + 4$, explicit analysts' forecasts are obtained from *I/B/E/S*,

if available. Explicit forecasts are almost always available for year $t + 1$ but are usually unavailable for the long-term horizons, years $t + 2$ through $t + 4$. If an explicit forecast is not available, we calculate a forecast as follows:

$$\text{ANEPS}_{t+\tau} = \text{ANEPS}_{t+s} \times (1 + \text{LTG})^{\tau-s}$$

where ANEPS_{t+s} is the *I/B/E/S* median consensus analysts' EPS forecast for year $t + s$ (the last year with an explicit EPS forecast), *LTG* is the median consensus analysts' long-term earnings growth rate forecast on *I/B/E/S*, $\tau = 1, \dots, 4$, $s = 0, \dots, 3$, and $\tau > s$.⁷ In this chapter, usually the second year's (year $t + 1$) explicit EPS forecast is compounded at the long-term earnings growth rate to calculate the analysts' long-term earnings forecast. The compounding of the second year's analysts' earnings forecast with the analysts' long-term earnings growth rate to calculate the subsequent years' analyst earnings forecasts is common in the literature (Claus & Thomas, 2001; P. Easton et al., 2002; Frankel & Lee, 1998; Gebhardt, Lee, & Swaminathan, 2001; Hribar & Jenkins, 2004; and others).

We also produce earnings forecasts using two naïve statistical models, namely, a RW model and a RW with a drift based on past economic growth rate (RWGDP) model. The RW model is specified as follows:

$$\text{RW}_{t+\tau} = \text{EPS}_{t-1}$$

where EPS_{t-1} is last year's actual EPS, and $\tau = 0, \dots, 4$.

The RWGDP model is specified as follows:

$$\text{RWGDP}_{t+\tau} = \text{EPS}_{t-1}(1 + g)^{\tau+1}$$

where g = historical inflation rate + historical growth in real GDP, and $\tau = 0, \dots, 4$. The growth rate g is determined using the inflation rate and the growth in real GDP for year $t - 1$. The historical inflation rate is retrieved from the Inflationdata.com web site (Capital Professional Services, 2009). The historical growth rate of GDP is based on GDP data at the web site of the U.S. Department of Commerce, Bureau of Economic Analysis (U.S. Department of Commerce, 2009).

We also calculate earnings forecasts using a hybrid (RWLTG) model that combines a RW based on prior year EPS with the analysts' long-term earnings growth forecast. The model is estimated as follows:

$$\text{RWLTG}_{t+\tau} = \text{EPS}_{t-1}(1 + \text{LTG})^{\tau+1}$$

where *LTG* is the *I/B/E/S* median consensus analysts' long-term earnings growth rate forecast, and $\tau = 0, \dots, 4$.

An additional issue arises if $ANEPS_{t+s}$ is negative for ANEPS calculations that require analysts' long-term earnings growth forecasts or if EPS_{t-1} is negative for the RWGDP and RWLTG models. First, it is unrealistic to assume that a firm can sustain an increasingly negative EPS over the forecast horizon. Second, positive earnings growth forecasts are meant to convey earnings increases. Therefore, when $ANEPS_{t+s}$ or EPS_{t-1} is negative, we use the negative of the growth rate in formulating the forecast. This implies a reversion toward zero earnings for future periods if the growth rate is positive (most cases). For example, using the RWLTG model as an illustration and assuming that EPS_{t-1} is $-\$1.00$ and LTG is 10%; $RWLTG_t$ is $-\$0.90$, $RWLTG_{t+1}$ is $-\$0.81$, $RWLTG_{t+2}$ is $-\$0.73$, and so on.

Measurement of Forecast Accuracy and Forecast Bias

To compare the forecast accuracy between analysts and naïve models, we calculate forecast error (FE) and relative forecast accuracy (RFA). We use two alternative deflators to calculate FEs. Specifically, we measure FE deflated by price (FE/P) as follows:

$$\frac{|EPS_{t+\tau} - ANEPS_{t+\tau} \text{ (or STATEPS}_{t+\tau})|}{P_{t-1}} \tag{1}$$

and FE deflated by forecasted EPS (FE/EPS) as follows:

$$\frac{|EPS_{t+\tau} - ANEPS_{t+\tau} \text{ (or STATEPS}_{t+\tau})|}{|ANEPS_{t+\tau} \text{ (or STATEPS}_{t+\tau})|} \tag{2}$$

where $EPS_{t+\tau}$ is future actual EPS, $STATEPS_{t+\tau}$ is the earnings forecast generated by one of the naïve models or the hybrid model discussed above, P_{t-1} is the stock price per share for the end of May, the month previous to the base month, and $\tau = 0, \dots, 4$.

We also measure the RFA, which directly compares the FE from the analysts' forecast with that from the naïve forecast. RFA deflated by price (RFA/P) is measured as follows:

$$\frac{(|EPS_{t+\tau} - ANEPS_{t+\tau}| - |EPS_{t+\tau} - STATEPS_{t+\tau}|)}{P_{t-1}}$$

while RFA deflated by EPS (RFA/E) is calculated as follows:

$$\frac{(|\text{EPS}_{t+\tau} - \text{ANEPS}_{t+\tau}| - |\text{EPS}_{t+\tau} - \text{STATEPS}_{t+\tau}|)}{|\text{EPS}_{t+\tau}|}$$

A negative (positive) RFA value implies higher analyst (model) forecast accuracy.

The RFA measure differs from the FE measure. For FE, we calculate the absolute values of earnings FEs of analysts and those of a particular model at the individual observation level and then determine the significance of the difference in means (medians) between the two groups of FEs using a *t*-test (sign test). For RFA, we take the difference in the absolute FEs of analysts and the applicable model at the individual observation level and then measure whether the mean (median) of these differences is significantly different from zero through a *t*-test (sign test). FE and RFA serve as alternative measures of earnings forecast accuracy. The FEs above 1.0 are winsorized at 1.0 and the RFA measures are winsorized at +1.0 and -1.0 (Brown et al., 1987a; Fried & Givoly, 1982).

Testing Information Content of Analysts' Forecasts versus Model Forecasts

The above measures of forecast accuracy examine the magnitudes of the deviations of the forecasted earnings from the actual earnings. However, given the earnings forecast with higher accuracy, the earnings forecast with lower accuracy may also contain incrementally useful information in predicting future earnings. For instance, if analysts misestimate the persistence of the prior year's earnings, then a naïve model using the prior year's earnings would likely contain information incremental to that from analysts' forecasts even if analysts' forecasts happen to be more accurate. To explore the information content of analysts' forecasts and model forecasts, we run the following regression using OLS (Cheng et al., 2003; Granger & Newbold, 1973):

$$\frac{\text{EPS}_{t+\tau}}{\text{EPS}_{t-1}} - \frac{\text{STATEPS}_{t+\tau}}{\text{EPS}_{t-1}} = \alpha + \beta \left(\frac{\text{ANEPS}_{t+\tau}}{\text{EPS}_{t-1}} - \frac{\text{STATEPS}_{t+\tau}}{\text{EPS}_{t-1}} \right) + \varepsilon_{t+\tau} \quad (3)$$

where EPS is actual EPS, ANEPS is the analysts' forecast, STATEPS is the earnings forecast from one of the naïve models or the hybrid model, and $\tau = 0, \dots, 4$. If all information in forecasting future actual earnings is provided by ANEPS, then β will equal one. On the contrary, if all information is provided by STATEPS, then β will equal zero. When information is provided by both ANEPS and STATEPS, $0 < \beta < 1$. It is

possible that β could be greater than one or less than zero. In these situations, both forecasts have information content in explaining future earnings but investors put a negative weight on one of the forecasts.

Although Granger and Newbold (1973) hypothesize that the intercept term is zero, we follow Cheng et al. (2003) and include an intercept term to account for any bias in analysts' forecasts. To reduce excessive influence from outliers, we do two procedures. First, we winsorize the dependent variable and the independent variable at $+1.0$ and -1.0 . Second, we eliminate outliers based on the guidelines of Belsley, Kuh, and Welsch (1980).

RESULTS

Full Sample

Panel A of Table 1 compares the earnings forecasts made by analysts with those from the RW model. The number of observations is lower for FE/P than FE/EPS due to the requirement of stock price from the CRSP database for FE/P.⁸ An analysis of FE/P and FE/EPS shows that, in forecasting short-term earnings (years t and $t + 1$), analysts' forecasts have significantly lower FEs than the RW model forecasts. For long-term forecasts, the results are mixed based on the FE measures. The median (mean and median) FE/P (FE/EPS) values convey that analysts tend to be more accurate over years $t + 2$ through $t + 4$. However, the results show that the forecast advantage for analysts steadily declines as the forecast horizon is extended. In fact, mean FE/P is significantly lower for RW forecasts at the 1% level in year $t + 4$. An observation of RFA/P and RFA/EPS, which serve as alternative measures of forecast accuracy, confirms analyst superiority over the naïve model for short-term earnings forecasts. On the contrary, for years $t + 3$ and $t + 4$ (years $t + 2$ through $t + 4$), the positive mean values of RFA/P (RFA/EPS) signify that RW model forecasts are significantly more accurate at the 1% level. Nevertheless, the median values of RFA/P and RFA/EPS convey that analysts' forecasts are significantly more accurate than RW forecasts for all forecast horizons. Overall, analysts' forecasts outperform the RW model in forecasting short-term earnings. However, the conflicting forecast accuracy results do not support the superiority of either analysts or the RW model in forecasting long-term earnings, especially for years $t + 3$ and $t + 4$.

We also compute forecast bias, which is measured using Eqs. (1) and (2) except that the numerators are signed values instead of absolute values.

Table 1. Comparison of Forecasts between Analysts and Naïve Models.

		Mean					Median				
		Year t	$t+1$	$t+2$	$t+3$	$t+4$	Year t	$t+1$	$t+2$	$t+3$	$t+4$
<i>Panel A: Analysts' forecasts versus random walk model</i>											
FE/P	Analysts	2.036	3.885	4.941	5.881	7.056	0.408	0.981	1.374	1.816	2.312
	RW	3.198	4.453	4.966	5.615	6.340	0.833	1.376	1.751	2.143	2.478
	Difference	-1.161***	-0.568***	-0.025	0.266	0.716***	-0.426***	-0.395***	-0.378***	-0.327***	-0.166***
	N	12,527	12,248	10,959	10,820	10,782					
FE/EPS	Analysts	26.148	40.089	46.933	50.987	54.754	11.364	24.655	33.846	41.156	48.966
	RW	36.668	45.906	50.229	53.380	55.902	22.857	35.189	42.188	47.945	52.105
	Difference	-10.520***	-5.816***	-3.297***	-2.393***	-1.148***	-11.494***	-10.534***	-8.341***	-6.789***	-3.139***
	N	27,079	26,383	23,127	22,762	22,615					
RFA/P		-1.221***	-0.607***	0.030	0.393***	0.909***	-0.324***	-0.359***	-0.352***	-0.409***	-0.387***
RFA/EPS		-13.093***	-0.867***	6.896***	10.497***	13.693***	-9.756***	-9.155***	-6.500***	-5.438***	-2.166**
<i>Panel B: Analysts' forecasts versus random walk with economic growth model</i>											
FE/P	Analysts	2.036	3.885	4.941	5.881	7.056	0.408	0.981	1.374	1.816	2.312
	RW/GDP	3.103	4.356	4.849	5.495	6.200	0.757	1.230	1.531	1.865	2.198
	Difference	-1.067***	-0.470***	0.092	0.386**	0.856***	-0.350***	-0.248***	-0.158***	-0.049	0.114**
	N	12,527	12,248	10,959	10,820	10,782					
FE/EPS	Analysts	26.148	40.089	46.934	50.989	54.756	11.364	24.648	33.849	41.165	48.968
	RW/GDP	35.731	44.723	48.856	51.761	54.081	21.152	32.743	39.477	44.618	49.138
	Difference	-9.583***	-4.634***	-1.922***	-0.772**	0.675**	-9.789***	-8.094***	-5.628***	-3.453***	-0.170
	N	27,081	26,384	23,128	22,763	22,616					
RFA/P		-1.119***	-0.481***	0.214***	0.550***	1.098***	-0.210***	-0.183***	-0.111**	-0.081**	0.027
RFA/EPS		-12.702***	-1.315***	6.433***	10.537***	14.671***	-6.695***	-5.032***	-1.938***	-0.045	3.335***

Notes: All values are shown as percentages. FE/P is forecast error deflated by price, specified as $(|EPS_{t+\tau} - ANEPS_{t+\tau} \text{ (or STATEPS}_{t+\tau})|) / P_{t-1}$, where EPS is actual annual earnings per share, ANEPS is analyst forecasted earnings per share, STATEPS is earnings per share estimated with one of the naive models, and P is stock price per share. FE/EPS is forecast error deflated by earnings per share, specified as $(|EPS_{t+\tau} - ANEPS_{t+\tau} \text{ (or STATEPS}_{t+\tau})|) / ANEPS_{t+\tau} \text{ (or STATEPS}_{t+\tau})$, where EPS is actual annual earnings per share, ANEPS is analyst forecasted earnings per share, and STATEPS is earnings per share estimated with one of the naive models. RFA/P is relative forecast accuracy deflated by price, specified as $(|EPS_{t+\tau} - ANEPS_{t+\tau}| - |EPS_{t+\tau} - STATEPS_{t+\tau}|) / P_{t-1}$, where EPS is actual annual earnings per share, ANEPS is analyst forecasted earnings per share, STATEPS is earnings per share estimated with one of the naive models, and P is stock price per share. RFA/EPS is relative forecast accuracy deflated by earnings per share, specified as $(|EPS_{t+\tau} - ANEPS_{t+\tau}| - |EPS_{t+\tau} - STATEPS_{t+\tau}|) / EPS_{t+\tau}$, where EPS is actual annual earnings per share, ANEPS is analyst forecasted earnings per share, and STATEPS is earnings per share estimated with one of the naive models. The measures (FE/P, RFA/P, etc.) are winsorized at -1.0 (if applicable) and $+1.0$. ***Significance at the 0.01 level (two-tailed). **Significance at the 0.05 level (two-tailed). *Significance at the 0.10 level (two-tailed).

The untabulated statistics show that analysts' earnings forecast bias values indicate analyst optimism, which increases as the forecast horizon is extended. This is consistent with the literature. The RW forecasts convey that they are pessimistically biased, which is not surprising because the assumption with RW forecasts is no growth over prior year's earnings.

Table 1, panel B, compares analysts' earnings forecasts with forecasts from the RWGDP model. Similar to the results in panel A, analysts are superior in forecasting short-term earnings. On the contrary, the findings are mixed with respect to long-term forecasts. An observation of mean FE/P shows that RWGDP long-term forecasts have lower FEs for year $t+3$ (at the 5% significance level) and year $t+4$ (at the 1% significance level). The results for median FE/P convey that analysts' FEs are significantly lower at the 1% level for year $t+2$, there is no significant difference for year $t+3$, and RWGDP model FEs are significantly lower at the 5% level for year $t+4$. The results for mean and median values of FE/EPS convey that analysts are more accurate for years t through $t+3$. However, the findings with respect to mean (median) values of FE/EPS in year $t+4$ indicate lower RWGDP model FEs (no significant difference in FEs). Turning to the alternative measures of forecast accuracy, the positive mean values of RFA/P and RFA/EPS for years $t+2$ through $t+4$ imply that RWGDP long-term forecasts are significantly more accurate at the 1% level. The median values of RFA/P indicate higher accuracy for analysts' forecasts in years $t+2$ and $t+3$ (at the 5% level) and no significant difference in year $t+4$. The median values of RFA/EPS show that while analysts are significantly more accurate at the 1% level in year $t+2$, there is no significant difference in year $t+3$, and the RWGDP model has significantly higher accuracy at the 1% level in year $t+4$. Overall, the results in panel B do not support the conjecture that analysts outperform the RWGDP model in making long-term earnings forecasts. Also, the accuracy of RWGDP model forecasts improves relative to analysts' forecasts as the forecast horizon is extended. The results provide some evidence on the superiority of RWGDP model forecasts over analysts' forecasts for year $t+4$.

The regression results from Eq. (3) with analysts' earnings forecasts and RW earnings forecasts are listed in Table 2, panel A.⁹ The parameter β is significantly greater than zero for all forecast periods, indicating that analysts' forecasts have information content in explaining future actual earnings. However, β is also significantly less than one for all forecast horizons, which implies that RW forecasts provide incremental information over analysts' forecasts. The value of β is 0.82 in year t , which conveys that analysts' forecasts for the first year play more of a role in assimilating information about future earnings than do RW model forecasts.

Table 2. Regression Analysis of Information Content of Analysts' Forecasts versus Naïve Model Forecasts.

Forecast Period	α		β	
	Coefficient	p -Value	Coefficient	p -Value
<i>Panel A: Analysts' forecasts versus random walk model</i>				
t	-0.05	0.00	0.82	0.00
$t+1$	-0.08	0.00	0.64	0.00
$t+2$	-0.05	0.00	0.50	0.00
$t+3$	-0.02	0.00	0.46	0.00
$t+4$	0.00	0.69	0.42	0.00
<i>Panel B: Analysts' forecasts versus random walk with economic growth model</i>				
t	-0.06	0.00	0.81	0.00
$t+1$	-0.11	0.00	0.64	0.00
$t+2$	-0.12	0.00	0.52	0.00
$t+3$	-0.13	0.00	0.49	0.00
$t+4$	-0.14	0.00	0.46	0.00

Notes:

1. The regression model is as follows:

$$\frac{\text{EPS}_{t+\tau}}{\text{EPS}_{t-1}} - \frac{\text{STATEPS}_{t+\tau}}{\text{EPS}_{t-1}} = \alpha + \beta \left(\frac{\text{ANEPS}_{t+\tau}}{\text{EPS}_{t-1}} - \frac{\text{STATEPS}_{t+\tau}}{\text{EPS}_{t-1}} \right) + \varepsilon_{t+\tau}$$

where EPS is actual annual earnings per share, ANEPS is the analysts' earnings per share forecast, STATEPS is the earnings per share forecast from one of the naïve models (random walk, random walk with economic growth), and $\tau=0, \dots, 4$.

2. The dependent and independent variables are winsorized at +1.0 and -1.0. Furthermore, outliers are eliminated using the techniques in Belsley et al. (1980).

3. The p -values show the significance of the difference from zero.

Nevertheless, the coefficient β steadily decreases as the forecast horizon is extended. Its value is 0.50, 0.46, and 0.42 for years $t+2$, $t+3$, and $t+4$, respectively. The substantially lower coefficients in years $t+2$ through $t+4$ suggest that for longer-term forecasts, much of the information content in explaining future actual earnings originates from the RW model instead of analysts' forecasts. This is likely in part due to (1) less of a timing advantage for analysts in forecasting long-term earnings as opposed to short-term earnings and (2) analysts' high optimism in forecasting long-term earnings.

Table 2, panel B, presents the results from regression Eq. (3) with RWGDP as the naïve model. The results are similar to those in panel A, where RW is the naïve model. The coefficient β in panel B does have a slightly smaller (larger) value than the corresponding coefficient in panel A for year t (years $t+2$ through $t+4$). A two-tailed t -test shows that the difference in coefficients is significant for year t at the 1% level and year $t+2$ at the 5% level.¹⁰ This implies that RWGDP model earnings forecasts contain slightly more (less) information in explaining future earnings that is not in analysts' earnings forecasts than do RW model earnings forecasts for years t (year $t+2$). Furthermore, for years t through $t+4$ in panel B, we find that the coefficient α is significantly less than zero, which is indicative of an optimistic bias in analysts' forecasts.

Sample Partitions and Hybrid Model

Prior research (e.g., Alford & Berger, 1999; Chan et al., 2003) suggests that the performance of financial analysts versus naïve models may be influenced by various attributes. Therefore, we evaluate the performance of analysts' earnings forecasts versus RWGDP model earnings forecasts across different sample partitions. The sample partitions are based on past earnings growth, analyst coverage, and a subsample with only explicit analysts' forecasts. Also, we compare the hybrid model, RWLTG, with the RWGDP model and analysts' forecasts. The objective is to determine whether improvements in accuracy and information content can be achieved by applying the analysts' forecasted long-term earnings growth rate to last year's (year $t-1$) earnings. For brevity, of the naïve models, we analyze only the RWGDP model in these additional tests because it is the most accurate.

Partitioning on Past Earnings Growth

Chan et al. (2003) show that very few firms are able to consistently achieve above-normal earnings growth over five years and the probability of doing so is about equal to pure chance. Furthermore, their findings suggest that financial analysts may incorrectly assume that past above-normal earnings growth will continue well into the future. However, the authors do not explicitly test this conjecture. If analysts often assume that high past earnings growth will continue well into the future, then based on findings in Chan et al. (2003), we would expect analysts' earnings forecasts for high past growth firms to have less accuracy, more bias, and less information content in explaining future actual earnings.

To test whether higher past earnings growth affects the performance of analysts' earnings forecasts relative to naïve forecasts (specifically, the RWGDP forecasts), we partition our sample according to past earnings growth. Past earnings growth is measured as the geometric growth in earnings between year $t-5$ and year $t-1$. It is necessary to mention two limitations of using the past geometric growth rate. First, only sample firms with positive year $t-5$ and positive year $t-1$ earnings can be used. Second, only firms with sufficient earnings histories are included. This may favor analysts' forecasts over RWGDP model forecasts because analysts tend to make more accurate forecasts for firms that are more mature. Firms with earnings growth rates above (below) the median level of 8.63% are designated as high (low) growth firms. This median growth rate is determined before observations are eliminated due to missing future actual earnings.

Table 3, panel A and panel B, presents the results for high and low past earnings growth firms, respectively. There are fewer observations in panel B because the low past growth subsample includes more firms that were in financial trouble, which means more bankruptcies and delistings and fewer observations with five years of future actual earnings. For both high past growth and low past growth firms, the majority of the FE (FE/P and FE/EPS) and RFA (RFA/P and RFA/EPS) values show that analysts are more accurate than the RWGDP model in forecasting short-term (year t and year $t+1$) earnings.

The nature of the findings changes for long-term earnings forecasts, which are the focus of our analysis. A comparison of panels A (high past earnings growth) and B (low past earnings growth) shows that the performance of analysts tends to improve relative to the RWGDP model when the past earnings growth is low. For the high past earnings growth subsample, the mean (median) FE measures FE/P, FE/EPS, RFA/P, and RFA/EPS imply consistently *lower* RWGDP model FEs than analysts' FEs at the 1% level over years $t+3$ and $t+4$ (year $t+4$). However, for low past earnings growth firms, the results are mixed with the mean RFA/EPS measure indicating lower FE for the RWGDP model and the median FE/P, FE/EPS, RFA/P, and RFA/EPS measures indicating lower errors for analysts' forecasts for years $t+2$ through $t+4$. Overall, for firms with high past earnings growth, the results imply a lower level of accuracy for financial analysts' earnings forecasts compared to the naïve RWGDP model forecasts for years $t+3$ and $t+4$. On the contrary, for firms with low past earnings growth, the results are mixed.

Table 3. Comparison of Forecasts between Analysts and Random Walk with Economic Growth Model; Observations Partitioned by Past Earnings Growth.

		Mean					Median				
		Year t	$t+1$	$t+2$	$t+3$	$t+4$	Year t	$t+1$	$t+2$	$t+3$	$t+4$
<i>Panel A: High past earnings growth</i>											
FE/P	Analysts	1.238	2.821	4.024	4.885	6.211	0.267	0.714	1.161	1.535	2.155
	RWGDP	1.936	3.010	3.677	4.165	5.072	0.526	0.926	1.229	1.462	1.808
	Difference	-0.698***	-0.189	0.347*	0.720***	1.139***	-0.259***	-0.212***	-0.068	0.073	0.347***
	N	4,846	4,790	4,523	4,485	4,473					
FE/EPS	Analysts	17.852	32.613	41.495	46.566	51.341	6.937	16.667	25.940	33.215	41.152
	RWGDP	24.978	35.300	40.612	43.836	46.639	13.250	22.188	28.674	33.128	36.779
	Difference	-7.126***	-2.687***	0.883	2.730***	4.702***	-6.313***	-5.521***	-2.734***	0.087	4.373***
	N	8,244	8,130	7,672	7,621	7,600					
RFA/P		-0.766***	-0.163*	0.431***	0.905***	1.433***	-0.183***	-0.169***	-0.054**	0.052	0.306***
RFA/EPS		-10.627***	-1.426***	7.066***	12.654***	18.181***	-5.487***	-4.648***	-0.803	2.867***	8.417***
<i>Panel B: Low past earnings growth</i>											
FE/P	Analysts	1.494	2.801	3.497	4.043	4.798	0.379	0.872	1.160	1.464	1.865
	RWGDP	2.307	3.125	3.479	4.017	4.536	0.706	1.085	1.397	1.725	2.012
	Difference	-0.813***	-0.324**	0.018	0.026	0.262	-0.327***	-0.213***	-0.237***	-0.261***	-0.147**
	N	4,636	4,556	4,175	4,134	4,119					
FE/EPS	Analysts	24.806	36.295	41.197	43.935	46.458	10.345	20.690	26.186	30.751	34.877
	RWGDP	33.659	40.624	44.161	47.236	49.376	20.201	29.240	34.544	39.998	43.479
	Difference	-8.853***	-4.329***	-2.964***	-3.301***	-2.918***	-9.856***	-8.550***	-8.358***	-9.247***	-8.602***
	N	7,667	7,530	6,888	6,834	6,812					
RFA/P		-0.833***	-0.373***	0.068	0.092	0.228**	-0.195***	-0.149***	-0.130***	-0.131***	-0.127***
RFA/EPS		-10.267***	0.511	5.119***	6.500***	7.879***	-5.324***	-3.830***	-2.841***	-2.783***	-2.461***

Notes: All values are shown as percentages. For the observations on the *I/B/E/S* database for June of each year from 1988 to 2007 that have the prior five years of earnings, we find the geometric growth rate in earnings from year $t-5$ to year $t-1$. Panel A (B) presents the results for sample observations with above (below) median prior earnings growth. The forecast measures (FE/P, RFA/P, etc.) are winsorized at -1.0 (if applicable) and $+1.0$. For variable definitions, see Table 1. ***Significance at the 0.01 level (two-tailed). **Significance at the 0.05 level (two-tailed). *Significance at the 0.10 level (two-tailed).

The untabulated bias statistics suggest that for short-term forecasts (years t and $t + 1$), analysts' forecasts are less optimistically biased for high past growth firms compared with low past growth firms. However, for longer horizons, analysts' forecasts are more optimistically biased for high past growth firms than low past growth firms, and the difference becomes larger as the forecast horizon is extended. Although financial analysts may often be correct to assume that high past earnings growth will continue over the short term, the bias results imply that analysts may tend to incorrectly assume that high past earnings growth will continue well into the future. This is further supported by the FE (FE/P and FE/EPS) statistics for analysts in Table 3. Although analysts' FEs tend to be lower for high past growth firms in years t and $t + 1$, they are clearly higher for high past growth firms in years $t + 3$ and $t + 4$.¹¹

Table 4 summarizes the results from regression Eq. (3) with panel A presenting the results for high past earnings growth firms and panel B displaying the findings for low past earnings growth firms. The coefficient β is higher for high past growth firms for forecast horizons t and $t + 1$. However, the situation reverses in years $t + 2$ through year $t + 4$. The differences are significant at the 1% level for all years except year $t + 2$. These results imply that analysts' forecasts have more incremental information content over the RWGDP model in explaining long-term future actual earnings for low past growth firms than for high past growth firms.

Partitioning on Analyst Following

Prior research (Alford & Berger, 1999; Brown, 1997; Coën, Desfleurs, & L'Her, 2009; Lim, 2001; Lys & Soo, 1995) provides evidence that higher analyst following is associated with greater analyst forecast accuracy. Analysts tend to follow firms with information that is more extensive and accurate. This reduces the uncertainty about the firms' prospects and helps analysts to make more accurate earnings forecasts. We partition our sample according to analyst following and examine the performance of analysts' long-term forecasts and the RWGDP model for the subsamples. Firm years with long-term growth forecasts from more than three (three or fewer) analysts are considered firms with high (low) analyst following.

Untabulated results show that both analysts' forecasts and RWGDP model forecasts are more accurate when there is high analyst following compared with low analyst following. This result is consistent with Previts, Bricker, Robinson, and Young (1994), who show that financial analysts tend to follow firms that smooth earnings. If firms smooth earnings, they

Table 4. Regression Analysis of Information Content of Analysts' Forecasts versus Random Walk with Economic Growth Model; Observations Partitioned by Past Earnings Growth.

Forecast Period	α		β	
	Coefficient	p -Value	Coefficient	p -Value
<i>Panel A: High past earnings growth</i>				
t	-0.05	0.00	0.99	0.00
$t+1$	-0.12	0.00	0.72	0.00
$t+2$	-0.14	0.00	0.51	0.00
$t+3$	-0.14	0.00	0.42	0.00
$t+4$	-0.17	0.00	0.40	0.00
<i>Panel B: Low past earnings growth</i>				
t	-0.07	0.00	0.81	0.00
$t+1$	-0.10	0.00	0.63	0.00
$t+2$	-0.10	0.00	0.54	0.00
$t+3$	-0.11	0.00	0.55	0.00
$t+4$	-0.13	0.00	0.57	0.00

Notes:

1. For observations on the *I/B/E/S* database for June of each year from 1988 to 2007 that have five prior years of earnings, we find the geometric growth rate in earnings from year $t-5$ to year $t-1$. Panel A (B) presents the results for observations with above (below) median prior earnings growth.
2. The regression model is as follows:

$$\frac{\text{EPS}_{t+\tau} - \text{RWGDP}_{t+\tau}}{\text{EPS}_{t-1} - \text{RWGDP}_{t-1}} = \alpha + \beta \left(\frac{\text{ANEPS}_{t+\tau} - \text{RWGDP}_{t+\tau}}{\text{EPS}_{t-1} - \text{RWGDP}_{t-1}} \right) + \varepsilon_{t+\tau}$$

where EPS is actual annual earnings per share, ANEPS is the analysts' earnings per share forecast, RWGDP is the earnings per share forecast from the random walk with economic growth model, and $\tau = 0, \dots, 4$.

3. The dependent and independent variables are winsorized at +1.0 and -1.0. Furthermore, outliers are eliminated using the techniques in [Belsley et al. \(1980\)](#).
4. The p -values test the significance of the difference from zero.

are easier to predict by analysts and a RW with a drift model such as RWGDP should be more accurate. Furthermore, for long-term earnings forecasts, the findings on accuracy convey that analysts' forecasts moderately improve relative to RWGDP model forecasts when there is

high analyst following. The results from regression Eq. (3) show that the coefficient β is significantly larger at the 1% level for the high analyst following subsample than for the low analyst following subsample for all five years. These results imply that financial analysts' forecasts have more information content in explaining future actual earnings for firms with high analyst coverage.

Explicit Analysts' Forecasts

Due to a scarcity of explicit analysts' long-term earnings forecasts (e.g., fourth-year EPS is expected to be \$2.50), most of the long-term earnings forecasts are calculated through compounding the analysts' second-year earnings forecast with the analysts' long-term earnings growth rate. However, it is possible that the accuracy of analysts' forecasts versus naïve models is different when analysts make explicit forecasts. Therefore, we also run our tests using only explicit forecasts from analysts.

The untabulated results show that the number of explicit forecasts drops precipitously between year $t+1$ and year $t+2$. The FEs (FE/P and FE/EPS) indicate that both analysts' forecasts and RWGDP model forecasts are more accurate for years $t+3$ and $t+4$ for the explicit forecast sample compared with the results for the entire sample noted in Table 1, panel B. This conveys that analysts tend to issue explicit long-term forecasts when earnings are easier to predict. However, the accuracy of analysts' earnings forecasts relative to RWGDP model forecasts for year $t+2$ does not improve when analysts make explicit forecasts. Nonetheless, when analysts make explicit forecasts, there is improvement in the accuracy of analysts' forecasts relative to RWGDP model forecasts for year $t+4$. On the contrary, explicit analysts' for year $t+4$ are scarce. For instance, there are only 1,323 (1,939) year $t+4$ explicit analysts' forecasts available when stock price (EPS) is the deflator. The untabulated regression results are in line with the forecast accuracy results. When analysts make explicit forecasts, the Eq. (3) coefficient β for year $t+2$ ($t+4$) is significantly less (greater) than the corresponding coefficient value in Table 2, panel B, at the 1% level.

Hybrid Model Forecasts

We compare the hybrid model, RWLTG, with the RWGDP model and analysts' earnings forecasts through variations of the previously discussed tests of accuracy and information content. Untabulated results show that combining a naïve model with analysts' long-term earnings growth rate forecasts does not improve forecast accuracy. In matching RWLTG against

RWGDP, median (mean) values indicate that the RWLTG (RWGDP) model is more accurate in forecasting short-term earnings. However, the RWLTG model is inferior to the RWGDP model in long-term earnings forecast accuracy. In addition, the RWLTG model is less accurate than analysts' forecasts in years t and $t + 1$. However, the difference in forecast accuracy gets smaller as the forecast horizon is extended. In fact, there is no significant difference in forecast accuracy between the RWLTG model and analysts' forecasts for year $t + 4$.

Untabulated regression results using the RWLTG and RWGDP models show that both models have incremental information content in explaining future actual earnings but that the RWGDP model has more information content. Similarly, although both analysts' earnings forecasts and the RWLTG model have incremental information content in explaining future actual earnings, analysts' forecasts have more information content.

CONCLUSIONS

We examine the performance of financial analysts versus naïve models in forecasting long-term earnings. Forecast performance is evaluated through analyzing forecast accuracy and information content. We find that analysts' long-term earnings forecasts (especially for the fourth year and fifth year in the forecast horizon) are often less accurate than forecasts from naïve models. Furthermore, both naïve model earnings forecasts and analysts' long-term earnings forecasts contain information content in predicting long-term earnings. Also, we find that the performance of analysts' forecasts declines relative to naïve model forecasts for subsamples of firms with high past earnings growth and low analyst following. When analysts make explicit earnings forecasts, the performance of analysts' forecasts increases compared to naïve model forecasts for only the fifth year in the forecast horizon. But explicit analysts' forecasts for the fifth year are scarce. Moreover, we test the accuracy and information content of a hybrid model that assumes a RW with a drift based on the analysts' long-term earnings growth rate. We find that this hybrid model is less accurate and has less information content in predicting long-term earnings than the RWGDP model or financial analysts.

Our findings imply that analysts' long-term earnings forecasts should be used with caution by researchers and practitioners as they do not appear to be more accurate than long-term forecasts from naïve models. Furthermore, the naïve models incorporate a large amount of information content useful

in explaining future actual earnings that is not in analysts' long-term earnings forecasts. Researchers and practitioners should be especially cautious when using analysts' long-term earnings forecasts for firms with high recent earnings growth. Furthermore, our findings indicate that it may be appropriate to use strong performing naïve models such as the RWGDP model or a pure RW model as a substitute for missing analysts' long-term earnings forecasts in applications such as implementing valuation models.

NOTES

1. Not all naïve forecasts are technically time series forecasts. For example, a pure RW forecast that uses the prior period's earnings as a forecast of future earnings is not a time series forecast because it is not based on a series of time periods. However, time series forecasts are naïve because they are mechanically based on past information. The term "time series forecast" is often used loosely in the literature.

2. For example, [Dechow et al. \(2000\)](#) examine the performance of analysts' long-term earnings growth forecasts that pertain to a sample of firms that recently issued equity.

3. The *I/B/E/S* database rarely provides forecast information pertaining to years after the fifth year.

4. The RW model assumes that future annual earnings will equal the most recent prior year's actual earnings.

5. We use June consensus forecasts because we use only December fiscal year-end firms. Thus, as of June, the previous year's financial results are likely to have been released. Also, the focus of this chapter is on long-term forecasts. The forecast month does not have as much of an impact on long-term forecasts as it would on short-term forecasts.

6. This requirement would likely favor analysts because they tend to forecast with more accuracy for firms that are more stable.

7. In defining the variables in this chapter, the firm subscript is suppressed.

8. It is only necessary to show the numbers of observations for the mean values of FE/P and FE/EPS because the numbers of observations are the same in the other related parts of the panel. There is a moderate drop in the number of observations between year $t + 1$ and year $t + 2$ because only short-term analysts' earnings forecasts are available for some firm years. Also, there is a slight decline in the number of observations over the long-term forecast horizons. As mentioned in the section on Analyst and Model Forecasts, we retrieve explicit EPS forecasts for the long-term horizons, if possible. Some firm years have a per share forecast for one or two long-term forecast period(s) (e.g., years $t + 2$ and $t + 3$) but not subsequent long-term forecast period(s) (e.g., year $t + 4$).

9. In the regression analyses in this chapter, we test for heteroskedasticity using methodology from [White \(1980\)](#) and find that heteroskedasticity is not a problem.

10. We use a two-tailed t -test to conduct statistical comparisons of the values of the coefficient β in panel A with those in panel B for [Tables 2 and 4](#). For the sake of

simplicity, we just discuss the results in the text and do not report the statistical significance in the tables.

11. We also determine analysts' long-term earnings growth rate forecasts for high and low past earnings growth firms. The mean (median) growth rate forecast is 15.37% (14.0%) and 12.55% (11.0%) for high and low past growth firms, respectively. The differences in the means and the medians are significant at the 1% level. Therefore, these findings show that analysts are more optimistic in their long-term earnings growth forecasts for firms with higher past earnings growth.

ACKNOWLEDGMENTS

We thank Jian Cao, Hui Du, Barry Marks, and Haeyoung Shin for their helpful comments and suggestions. Also, we thank participants at the 2010 American Accounting Annual Meeting and the 2010 Southwest Region American Accounting Association Annual Meeting for useful discussions. The second author acknowledges a 2009 summer research grant from the College of Business at Prairie View A&M University.

REFERENCES

- Alford, A. W., & Berger, P. G. (1999). A simultaneous equations analysis of forecast accuracy, analyst following, and trading volume. *Journal of Accounting, Auditing & Finance*, 14(Summer), 219–240.
- Allee, K. (2009). *Estimating cost of equity capital with time-series forecasts of earnings*. Working paper. Michigan State University, East Lansing, MI.
- Belsley, D., Kuh, E., & Welsch, R. (1980). *Regression diagnostics*. New York, NY: Wiley.
- Bhushan, R. (1989). Firm characteristics and analyst following. *Journal of Accounting and Economics*, 11(2–3), 255–274.
- Botosan, C., & Plumlee, M. (2005). Assessing alternative proxies for the expected risk premium. *The Accounting Review*, 80(January), 21–53.
- Bradshaw, M. (2004). How do analysts use their earnings forecasts in generating stock recommendations? *The Accounting Review*, 79(January), 25–50.
- Brown, L. (1993). Earnings forecasting research: Its implications for capital markets research. *International Journal of Forecasting*, 9, 295–320.
- Brown, L. (1997). Analyst forecasting errors: Additional evidence. *Financial Analysts Journal*, 53(November/December), 81–88.
- Brown, L., Griffin, P., Hagerman, R., & Zmijewski, M. (1987a). Security analyst superiority relative to time-series models in forecasting quarterly earnings. *Journal of Accounting and Economics*, 9, 61–87.
- Brown, L., Griffin, P., Hagerman, R., & Zmijewski, M. (1987b). An evaluation of alternative proxies for the market's assessment of unexpected earnings. *Journal of Accounting and Economics*, 9, 159–193.

- Brown, L., Richardson, G., & Schwager, S. (1987). An information interpretation of financial analyst superiority in forecasting earnings. *Journal of Accounting Research*, 25(Spring), 49–67.
- Brown, L., & Rozeff, M. (1978). The superiority of analyst forecasts as measures of expectations: Evidence from earnings. *Journal of Finance*, 33(March), 1–16.
- Capital Professional Services. (2009). InflationData.com. Historical US inflation rate 1914-present. Retrieved from http://inflationdata.com/Inflation/Inflation_rate/historicalinflation.aspx
- Chan, L., Karceski, J., & Lakonishok, J. (2003). The level and persistence of growth rates. *Journal of Finance*, 58(April), 643–684.
- Cheng, J., Fan, D., & So, R. (2003). On the performance of naïve, analyst and composite earnings forecasts: Evidence from Hong Kong. *Journal of International Financial Management & Accounting*, 14, 146–165.
- Claus, J., & Thomas, J. (2001). Equity Premia as low as three percent? Evidence from analysts' earnings forecasts for domestic and international stocks. *Journal of Finance*, 56, 1629–1666.
- Coën, A., Desfleurs, A., & L'Her, J. (2009). International evidence on the relative importance of the determinants of earnings forecast accuracy. *Journal of Economics and Business*, 61(6), 453–471.
- Conroy, R., & Harris, R. (1987). Consensus forecasts of corporate earnings: Analysts' forecasts and time series methods. *Management Science*, 33, 725–738.
- Cragg, J., & Malkiel, B. (1968). The consensus and accuracy of some predictions of the growth of corporate earnings. *Journal of Finance*, 23(March), 67–84.
- Dechow, P., Hutton, A., & Sloan, R. (2000). The relation between analysts' forecasts of long-term earnings growth and stock price performance following equity offerings. *Contemporary Accounting Research*, 17(Spring), 1–32.
- Easton, P., & Monahan, S. J. (2005). An evaluation of accounting-based measures of expected returns. *The Accounting Review*, 80, 501–538.
- Easton, P., & Sommers, G. (2007). Effect of analysts' optimism on estimates of the expected rate of return implied by earnings forecasts. *Journal of Accounting Research*, 45(5), 983–1015.
- Easton, P., Taylor, G., Shroff, P., & Sougiannis, T. (2002). Using forecasts of earnings to simultaneously estimate growth and the rate of return on equity investment. *Journal of Accounting Research*, 40(June), 657–676.
- Francis, J., Olsson, P., & Oswald, D. (2000). Comparing the accuracy and explainability of dividend, free cash flow, and abnormal earnings equity value estimates. *Journal of Accounting Research*, 38, 45–70.
- Frankel, R., & Lee, C. (1998). Accounting valuation, market expectation, and cross-sectional stock returns. *Journal of Accounting and Economics*, 25, 283–319.
- Fried, D., & Givoly, D. (1982). Financial analysts' forecasts of earnings: A better surrogate for market expectations. *Journal of Accounting and Economics*, 4, 85–107.
- Gebhardt, W., Lee, C., & Swaminathan, B. (2001). Toward an implied cost of capital. *Journal of Accounting Research*, 39(June), 135–176.
- Granger, C., & Newbold, P. (1973). Some comments on the evaluation of economic forecasts. *Applied Economics*, 5, 35–47.
- Hong, H., Lim, T., & Stein, J. (2000). Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies. *Journal of Finance*, 55, 265–295.

- Hou, K., van Dijk, M., & Zhang, Y. (2010). *The implied cost of capital: A new approach*. Working paper. Ohio State University, Erasmus University, and Chinese University of Hong Kong.
- Hribar, P., & Jenkins, N. T. (2004). The effect of accounting restatements on earnings revisions and the estimated cost of capital. *Review of Accounting Studies*, 9, 337–356.
- Imhoff, E., & Pare, P. (1982). Analysis and comparison of earnings forecast agents. *Journal of Accounting Research*, 20(Autumn), 429–439.
- Lim, T. (2001). Rationality and analysts' forecast bias. *Journal of Finance*, 56(1), 369–385.
- Lys, T., & Soo, L. G. (1995). Analysts' forecast precision as a response to competition. *Journal of Accounting, Auditing and Finance*, 10(Fall), 751–763.
- Newbold, P., Zumwalt, J., & Kannan, S. (1987). Combining forecasts to improve earnings per share prediction. *International Journal of Forecasting*, 3, 229–238.
- Previts, G., Bricker, R., Robinson, T., & Young, S. (1994). A content analysis of sell-side financial analyst company reports. *Accounting Horizons*, 8, 55–70.
- Ramnath, S., Rock, S. K., & Shane, P. B. (2008). The financial analyst forecasting literature: A taxonomy with suggestions for further research. *International Journal of Forecasting*, 24, 34–75.
- Rozeff, M. (1983). Predicting long-term earnings growth: Comparisons of expected return models, submartingales and value line analysts. *Journal of Forecasting*, 2, 425–435.
- Schipper, K. (1991). Analysts' forecasts. *Accounting Horizons*, 5, 105–131.
- Sougiannis, T., & Yaekura, T. (2001). The accuracy and bias of equity values inferred from analysts' earnings forecasts. *Journal of Accounting, Auditing and Finance*, 16(Fall), 331–362.
- Stickel, S. (1992). Reputation and performance among security analysts. *Journal of Finance*, 47(December), 1811–1836.
- Thomson Financial. (2004). Thomson Financial Glossary 2004: A Guide to Understanding Thomson Financial Terms and Conventions for the First Call and I/B/E/S Databases.
- U.S. Department of Commerce. (2009). Bureau of Economic Analysis website. Retrieved from <http://www.bea.gov/>
- White, H. (1980). A heteroscedasticity-consistent covariance matrix estimator and a direct test for heteroscedasticity. *Econometrica*, 48, 149–170.