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A re-examination of analysts' superiority over time-series forecasts of annual earnings

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Abstract We re-examine the widely held belief that analysts' earnings per share (EPS) forecasts are superior to random walk (RW) time-series forecasts. We investigate whether analysts' annual EPS forecasts are superior, and if so, under what conditions. Simple RW EPS forecasts are more accurate than analysts' forecasts over longer horizons, for smaller or younger firms, and when analysts forecast negative or large changes in EPS. We also compare the accuracy of a third forecast of longer-term earnings based on a naïve extrapolation of analysts' 1-year-ahead forecasts. Surprisingly, this naïve extrapolation provides the most accurate estimate of long-term (2- and 3-year-ahead) earnings. These findings recharacterize prior generalizations about the superiority of analysts' forecasts and suggest that they are incomplete, misleading, or both. Moreover, in certain settings, researchers can rely on forecasts other than these explicit forecasts.

Keywords Analyst forecasts · Time-series forecasts · Random walk · Analysts' superiority

JEL Classification G17 · M40 · M41

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1 Introduction

Research on analysts' forecasts originated from a need among capital markets researchers to find a reliable proxy for investor expectations of earnings per share (EPS). The need for a proxy arose from a growing interest in the relation between accounting earnings and stock returns that began with Ball and Brown (1968). During the two decades spanning approximately 1968 through 1987, many researchers examined whether analysts' forecasts were superior to time-series forecasts. This literature culminated with a conclusion in Brown et al. (1987b) that analysts' forecasts *are* superior to time-series forecasts because analysts possess both an *information* advantage and a *timing* advantage. Subsequently, there was a sharp decline in research on the properties of time-series forecasts. Indeed, in a review of the capital markets literature, Kothari (2001, p. 145) observes that the time-series properties of earnings literature is fast becoming extinct because of "the easy availability of a better substitute" which is "available at a low cost in machine-readable form for a large fraction of publicly traded firms."[1] Thus, it appears that academics have largely concluded that analysts' forecasts of annual earnings are superior to those from time-series models.[2]

In this paper, we re-examine the widely held belief that analysts' annual EPS forecasts are superior to those from time-series models. We do this by comparing the performance of simple random walk (RW) annual earnings forecasts and analysts' annual earnings forecasts. Given information and timing advantages (Brown et al. 1987b), it seems improbable that analysts would *not* provide more accurate forecasts than a simple RW model. However, analysts are subject to a number of well-known conflicts of interest that can result in biased or inaccurate forecasts (Francis and Philbrick 1993; Dugar and Nathan 1995; McNichols and O'Brien 1997; Lin and McNichols 1998). Moreover, prior research supporting the conclusion that analysts are superior is subject to numerous caveats that seem to have been underappreciated (for example, small samples, bias towards large firms, negligible economic significance, etc.).

First, the early studies examining analysts versus time-series models use very small samples by current research standards. For example, Brown and Rozeff (1978) use forecasts for only 50 firms from 1972 through 1975, and Fried and Givoly (1982)–arguably the most extensive sample in this early literature–use forecasts for only 424 firms from 1969 through 1979. These small samples result from the limited availability of machine readable data and the data demands of ARIMA models, which require a long time series of earnings (for example, 10–20 years) to estimate time-series parameters. Second, other common research design choices, such as the selection of only December fiscal year-end firms or only firms trading on the New

[1] Kothari (2001, p. 153) further states that "*conflicting evidence notwithstanding*, in recent years it is common practice to (implicitly) assume that analysts' forecasts are a better surrogate for market's expectations than time-series forecasts" [emphasis added].

[2] As noted in Bradshaw (2010), the accounting literature is unique in its conclusion that expert forecasts are superior to time-series forecasts. Findings from research in economics, genetics, and physics are largely consistent with time-series models outperforming experts (see e.g., Belongia 1987; Fintzen and Stekler 1999; Loungani 2000).

York Stock Exchange (which bias samples towards large, mature, and stable firms), may also affect early results. Finally, analysts generally follow larger firms with considerable institutional following (Bhushan 1989) and more extensive disclosures (Lang and Lundholm 1996). This limits the generalizability of the early evidence on analysts' forecast superiority, as was generally acknowledged by the authors of these studies through careful descriptions of their samples and other caveats.

Researchers now use analysts' earnings forecasts to proxy for the expected earnings of firms that are not well-represented in these early studies. For example, Lee (1992), Clement et al. (2003), and Jegadeesh and Livnat (2006) use analysts' forecasts to proxy for earnings expectations for small firms, which are not represented in the early studies of analysts' versus time-series forecasts. Similarly, researchers sometimes use analysts' forecasts of earnings over horizons also not represented in these early studies, which rarely examine forecast horizons beyond 1 year. For example, in the valuation and cost of capital literatures (for example, Frankel and Lee 1998; Claus and Thomas 2001; Gebhardt et al. 2001; Easton et al. 2002; and Hribar and Jenkins 2004), analysts' forecasts are often used to proxy for longer-horizon earnings expectations, such as 2- to 5-year-ahead earnings.[3] Easton and Sommers (2007) note that the use of analysts' forecasts introduces bias into implied cost of capital estimates, and they suggest that researchers use past earnings realizations instead of analyst forecasts to avoid this bias.

Our empirical tests are based on forecasts of annual earnings over horizons ranging from 1 through 36 months. We focus on annual (rather than quarterly) earnings because we are interested in evaluating analysts' superiority over both short and long forecast horizons and the availability of quarterly analysts' earnings forecasts is generally limited to several quarters ahead. Furthermore, it is unlikely that RW forecasts are superior to analysts' forecasts in the quarterly setting, where both the information and timing advantages of analysts are greatest.[4] Our focus on annual earnings forecasts is also consistent with the extensive use of these forecasts in research on the cost of equity capital and valuation.

We document several surprising findings. First, for longer forecast horizons, analysts' forecasts of future earnings are *not* consistently more accurate than time-series models, even when analysts have timing and information advantages. Second, for forecast horizons where analysts *are* more accurate than RW forecasts (that is, forecast horizons of several months), the differences in accuracy are economically small. Third, RW forecasts are more accurate than analysts' forecasts for estimating 2-year-ahead earnings in approximately half of the forecast horizons analyzed, and RW forecasts strongly dominate analysts' forecasts of 3-year-ahead earnings.

[3] One notable exception is Allee (2010), who uses 2-year-ahead annual forecasts combined with the Easton (2004) implementation of the Ohlson and Jeuttner-Nauroth (2005) earnings growth valuation model to reverse engineer the implied cost of equity capital. He finds that cost of equity capital estimates using time-series forecasts are reliably associated with risk proxies (e.g., market volatility, beta, leverage, size, book-to-price, etc.) and concludes that researchers and investors may use time-series forecasts of earnings to estimate the implied cost of equity capital for firms not covered by analysts.

[4] While we do not examine this conjecture, our near-term forecasts of annual earnings are analogous to quarterly forecasts for the fourth quarter and, for these very short forecast horizons, analysts indeed dominate time-series models.

Fourth, over longer forecast horizons, analysts' forecast superiority is prevalent only in limited settings, such as when analysts forecast negative changes or small absolute changes in EPS. These results conflict with common and often implicit assertions that analysts' forecasts are uniformly a better proxy for investor expectations than are forecasts from time-series models. The evidence that time-series forecasts perform as well or better than analysts' forecasts suggests that the generalizability of research typically confined to firms with available analysts' forecast data (that is, large, mature firms) would be enhanced by incorporating time-series forecasts, which permits an expansion of firms available to be examined.

Although the tenor of our conclusions appears to contradict those in early studies, we note that early research was deliberate in its sample selection and research design choices, and the conclusions were drawn appropriately. As in many literatures, it is the subsequent researcher who over-generalizes findings from prior literature (Bamber et al. 2000). Consistent with the early research, we find that, for large, mature, and stable firms, over relatively short horizons, analysts' forecasts consistently outperform forecasts from a RW model and from all of the other time-series models that we evaluate.[5] However, for all but the very shortest of forecast horizons, analysts' forecast superiority is economically small for the average firm. Moreover, for smaller firms and for firms with low analyst following, analysts' superiority is quite small. Over longer horizons, analysts' forecasts are *not* superior to RW forecasts.

In additional analyses, we compare the performance of RW and of analysts' forecasts of 2- and 3-year-ahead earnings to an alternative forecast (the "short-horizon" forecast). The short-horizon forecast uses the analysts' consensus forecast for year $T + 1$ as the estimate of EPS for years $T + 2$ and $T + 3$. We find that this naïve extrapolation of analysts' 1-year-ahead forecasts provides the most accurate forecast over almost every horizon and among all subsamples. Not only do short-horizon forecasts dominate analysts' explicit forecasts of year $T + 2$ and $T + 3$ earnings, but they also consistently outperform RW forecasts. Thus, researchers interested in estimating long-term earnings can obtain more accurate forecasts, on average, by using analysts' consensus 1-year-ahead forecasts to estimate earnings beyond year $T + 1$ (for example, for $T + 2$ and $T + 3$).

Our sample is necessarily limited to firms with available analyst forecasts. However, as we document, the population of firms without any analyst coverage has declined to a trivial segment of publicly traded firms. A second important design choice is that, because analysts forecast earnings which are purged of transitory or special items, we use actual earnings per I/B/E/S (rather than earnings from Compustat) to calculate analysts' forecast errors and RW forecast errors. This is necessary in order to make the analyst and RW forecast errors comparable. While researchers could use earnings calculated using Generally Accepted Accounting

[5] In untabulated analyses, we also find that RW forecasts are superior to forecasts from more complicated time-series models (e.g., RW with a drift) for two reasons. First, analysts are better at estimating earnings for firms with sufficient data to calculate the time-series parameters in complicated time-series models because longer time-series availability is characteristic of more mature firms. Second, adding time-series parameters to a RW forecast does not help much because the negative serial correlation in EPS changes is very small.

Principles adjusted for likely transitory components with similar results, this would essentially replicate the construction of the I/B/E/S actual earnings number that we use.

In Sect. 2, we review the prior literature. We describe our data and develop hypotheses in Sect. 3. We present test results in Sect. 4, and Sect. 5 concludes.

2 Prior research and motivation

2.1 Prior research

Numerous studies examine the time-series properties of annual earnings and generally find that annual earnings approximate a simple RW process (for example, Little 1962; Ball and Watts 1972; Albrecht et al. 1977; Watts and Leftwich 1977). Based on this evidence, Brown (1993, p. 295) concludes that earnings follow a RW and that this was "pretty much resolved by the late 1970s."[6] A stream of literature based on these prior studies compares the accuracy of time-series forecasts and analysts' forecasts. These studies can be broadly classified into two lines of research. The first line asks whether analysts' forecasts *are superior to* time-series forecasts. For example, Fried and Givoly (1982) argue that analysts' superiority derives from an *information advantage* because analysts have access to a broader information set, which includes non-accounting information as well as information released after the prior fiscal year. They report prediction errors of 16.4 percent using analysts' forecasts versus 19.3 percent using a modified sub-martingale RW model and 20.3 percent using a RW model. Differences among these prediction errors seem economically small but are statistically significant, which is consistent with similar studies. For example, using forecasts made four quarters prior to year-end, Collins and Hopwood (1980) find mean analysts' forecast errors of 31.7 percent compared with 32.9 percent for their most accurate time-series forecast (again, an economically small but statistically significant difference).

The second line of research investigates the *source* of this apparent superiority. For example, Brown et al. (1987c) find that analysts' forecast superiority is positively (negatively) related to firm size (forecast dispersion). Brown et al. (1987b) and several subsequent studies (for example, Kross et al. 1990; Lys and Soo 1995) find that analyst superiority is negatively related to the forecast horizon because analysts have access to information released after the date of the time-series forecast. Thus, they have a *timing advantage*. Finally, O'Brien (1988) argues that analysts' superiority stems from their use of time-series models along with a broader information set that includes information about industry and firm sales and production, general macroeconomic information, and other analysts' forecasts. Consistent with this, Kross et al. (1990) find that the analysts' advantage is positively associated with firm coverage in *The Wall Street Journal*.

[6] The RW model is also advantageous because it does not require a long time series of data, which restricts the sample size and induces survivor bias.

Table 1 summarizes 12 important studies on the performance of time-series versus analysts' forecasts and presents the sample size, time-period, time-series models investigated, data requirements, treatment of outliers, forecast horizon, and summary results. Several observations are noteworthy. First, these studies typically use time-series data from the 1960s and 1970s. Second, the sample sizes are small, ranging from 50 to a few hundred firms. Third, the time-series models require between 10 and 20 years of data. Fourth, the forecast horizons range from one quarter ahead in the quarterly setting to 18 months ahead in the annual setting, with most focused on quarterly forecasts. Fifth, forecast accuracy is generally evaluated using the absolute value of forecast errors scaled by actual EPS or stock prices. Sixth, while the reported differences in forecast accuracy are typically statistically significant and analysts generally win, the economic magnitudes of these differences are modest at best. Finally, the analysts' forecast advantage is positively associated with firm size and negatively associated with prior dispersion in analysts' forecasts and forecast horizon.

2.2 Why re-examine the relative forecast accuracy of analysts versus time-series models?

Our review of the accounting and finance literature above suggests that it took approximately two decades for the literature to conclude that analysts are better at predicting future earnings than are time-series models. As Kothari (2001) notes, due to this conclusion and the increased availability of analysts' forecast data in machine-readable form, the literature on time-series models quickly died.[7] However, this conclusion is primarily based on studies using small samples of large, mature, and stable firms, and although the margin of analysts' superiority over time-series forecasts is not overwhelming, analysts' forecasts are used pervasively in the literature to proxy for market expectations for all firms. This general reliance on analysts' forecasts contrasts with Walther (1997), who concludes that the market does not consistently use analysts' forecasts or forecasts from time-series models to form expectations of future earnings. Additionally, analysts may not be equally skilled at predicting earnings for large and small firms (or for firms that differ on other dimensions).

Another motivation for our re-examination is that many firms were not covered by analysts during the sample periods studied in earlier research and, therefore, are excluded from research that requires longer-term earnings forecasts. If analysts' forecasts over long horizons are not superior to time-series forecasts, then requiring that sample firms have analysts' forecasts unnecessarily limits the data upon which this research is based and hence is a costly restriction. To estimate the cost (in terms of sample exclusion) of requiring analysts' forecasts, we identify the number of firms with available financial and market data not included in I/B/E/S. Figure 1 plots of the percentage of public firms with available data in Compustat and in the

[7] Since the 1980s, the forecasting literature has focused on refinements to better understand various features of analysts' forecasts, such as the determinants of analysts' forecast accuracy (Clement 1999), bias in analysts' forecasts (Lim 2001), and the efficiency of analysts' forecasts with respect to public information (Abarbanell 1991).

Table 1 Prior literature

Paper	Sample and time period	Time-series (TS) models and data requirements	Outliers	Forecast horizon	Difference in forecast accuracy	Analysts' superiority determinants
Brown and Rozeff (1978)	50 firms from 1972 through 1975	Three TS models using quarterly data, requiring complete data for 20 years	Winsorized forecast errors at 1.0	1–5 quarters ahead	Median difference in forecast errors between all univariate forecasts and the analysts' forecast is significantly greater than zero	
Collins and Hopwood (1980)	50 firms from 1951 through 1974	Four TS models, requiring a minimum of 76 quarters of data	Winsorized forecast errors at 3.0	1–4 quarters ahead	Four quarters out, analysts' forecast errors are 31.7% compared with the best TS error of 32.9%. One quarter out, mean analysts' forecast error are 9.7% compared with the best TS error of 10.9%	
Fried and Givoly (1982)	424 firms from 1969 through 1979	Modified submartingale models, requiring a minimum of 10 years of past data	Winsorized forecast errors at 1.0	8 months prior to the fiscal end	Analysts' forecast errors are 16.4% of realized EPS compared to 19.3% for the best TS model	
Hopwood and McKeown (1982)	258 firms from 1974 through 1978	RW and 7 other TS models, requiring at least 12 years (48 quarters) of data		1–4 quarters ahead	Four quarters out (annual), absolute analysts' forecasts errors are 22.5% compared with absolute forecast errors of 26.1% for RW	Number of days separating TS and analysts' forecast—positive
Brown et al. (1987a)	233 firms from 1975 through 1980	3 TS models, requiring a minimum of 60 quarters of data	Winsorized forecast errors at 1.0	1, 2, and 3 quarters ahead	Three-quarters-ahead, analysts' forecast errors are 28.7% and TS forecast errors are 33%	Forecast horizon—negative

Table 1 continued

Paper	Sample and time period	Time-series (TS) models and data requirements	Outliers	Forecast horizon	Difference in forecast accuracy	Analysts' superiority determinants
Brown et al. (1987a)	Sample 1: 168 firms from Q1-1977 through Q4-1979	Quarterly RW model		1, 2, and 3 quarters ahead	For the 1 month horizon, the log of the squared ratio of TS to analysts' forecast errors is 0.56	Firm size—positive; Prior analysts' forecast dispersion—negative
Brown et al. (1987a)	Sample 2: 168 firms from 1977 through 1979	Annual RW model		Horizons of 1, 6, and 18 months prior to the fiscal year-end date	For the 1 month horizon, the log of the squared ratio of TS to analysts' forecast errors is 1.08	Firm size—positive; prior analysts' forecast dispersion—negative
Brown et al. (1987a)	Sample 3: 702 firms from 1977 through 1982	Annual RW model		Horizons of 1, 6, and 18 months prior to the fiscal year-end date	Log of the squared ratio of TS to analysts' forecast errors is 1.01 for the 1 month horizon	Firm size—positive; prior analysts' forecast dispersion—negative
O'Brien (1988)	184 firms from 1975 through 1982	Two TS models, requiring 30 consecutive quarters of data	Deleted absolute forecast errors larger than $10	Horizons of 5, 60, 120, 180, and 240 trading days prior to the earnings announcement date	At 240 trading days (1 year), analysts' forecast errors are $0.74 compared to TS forecast errors of $0.96	Forecast horizon—positive
Kross et al. (1990)	279 firms from 1980 through 1981	Box–Jenkins model, requiring 28 quarters of data		Last available one-quarter-ahead forecast	Natural log of 1 + absolute TS error—absolute analysts' error is positive across all industries (ranging from 0.043 to 0.385)	Earnings variability—positive; *Wall Street Journal* coverage—positive; # of days separating TS and analysts' forecasts—positive

Table 1 continued

Paper	Sample and time period	Time-series (TS) models and data requirements	Outliers	Forecast horizon	Difference in forecast accuracy	Analysts' superiority determinants
Lys and Soo (1995)	62 firms from 1980 through 1986	Box-Jenkins model, requiring 20 years of data	Removed one firm	Up to 8 quarters ahead	Across all horizons, the mean (median) absolute analysts' forecast error is 4.4% (2.8%), and the mean (median) absolute TS error is 26.8% (1.4%)	Forecast horizon—negative
Branson et al. (1995)	223 firms from 1988 through 1989	ARIMA model, requiring 11 years of complete data		One quarter ahead	The median absolute percentage forecast error [(actual − predicted)/actual] from TS minus analysts' forecasts is 7.22%	Conditional on the firm being small: earnings variability—positive; firm size—negative

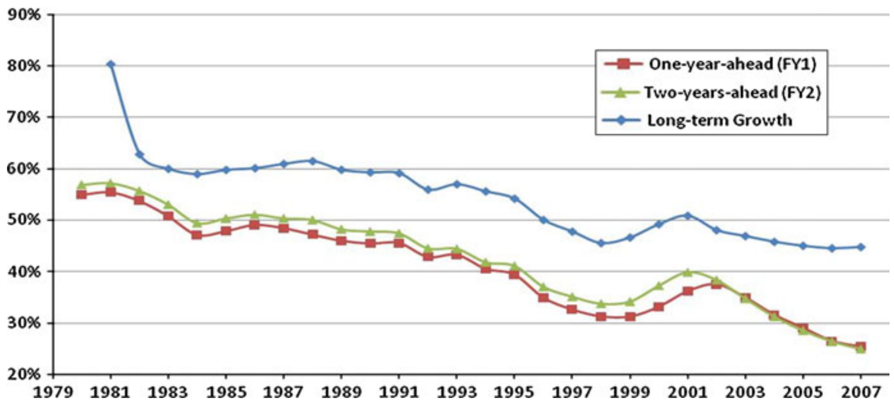

Fig. 1 Percentage of firms with available data in Compustat and CRSP that are uncovered in I/B/E/S

Center for Research in Securities Prices (CRSP) that *do not* have analysts' 1- and 2-year-ahead earnings forecasts and long-term growth forecasts available in I/B/E/S.[8] As illustrated in Fig. 1, the percentage of firms with available Compustat and CRSP data that did not have 1-year-ahead analyst forecast data in I/B/E/S was approximately 50 percent through the early 1990s but in recent years, this percentage has declined to approximately 25 percent. Although the costs may have attenuated due to increased coverage by analysts and/or I/B/E/S, there remains a discrepancy between the samples of firms analyzed in early research and those firms to whom these results are often generalized.

Finally, the results in Easton and Sommers (2007) also motivate our re-examination of analyst superiority. Easton and Sommers (2007) address researchers' frequent use of analyst forecasts, which are known to be optimistically biased, to estimate expected rates of return implied by stock prices, book values, and analyst earnings forecasts. They develop estimates of implied expect rates of return using analysts' 1-year-ahead forecasts or realized earnings. They find that the upward bias in expected rates of return when analysts' forecasts are used is statistically significant and economically meaningful. One practical implication offered by the authors is that future research can avoid this bias by estimating the rate of return implied by market prices, accounting book values, and past *realized* earnings rather than analysts' *forecasts* of earnings. Similar to Easton and Sommers (2007), our objective is to revisit the question of whether analysts' long-term earnings forecasts are superior to those based on realized earnings and to offer practical implications to researchers and practitioners interested in using forecasts of long-term earnings.

[8] We identify this sample by starting with all firms in Compustat with positive total assets. We retain all firms with monthly stock price data as of the fiscal-end month available from CRSP. Finally, we use I/B/E/S data to identify whether consensus forecast data as of the fiscal-end month are available for the remaining firms.

2.3 Empirical methodology

We compare the accuracy of analysts' forecasts of annual earnings with that of time-series forecasts, based on annual realizations, over various horizons ranging from 1 to 36 months prior to the earnings announcement date. We employ a RW time-series forecast for two reasons. First, very little evidence suggests that more sophisticated time-series models are more accurate than simple time-series models of annual earnings (Albrecht et al. 1977; Watts and Leftwich 1977; Brown et al. 1987b). Second, RW requires no parameter estimates and so does not impose the costly data demands of more complicated ARIMA models. Thus, using RW forecasts frees us from further data requirements that might skew our analyses to large, mature firms (as in prior research).[9]

Consistent with prior studies, we expect analysts' superiority to decrease as the forecast horizon increases (Brown et al. 1987b). Next, we investigate settings where we expect analysts to have less of an information advantage. That is, we compare the forecast accuracy of analysts' forecasts with that of RW forecasts for young firms, small firms, and firms with low analyst following. We also examine whether the outcome of comparisons is affected in settings where analysts forecast positive versus negative changes in EPS and when they forecast large versus small changes in EPS.[10]

3 Data

We first collect data from the I/B/E/S consensus file and from the Compustat annual file. Our sample spans 1983 through 2008. We impose minimal constraints on data availability. For a firm-year observation to be included, the prior year's EPS, at least one earnings forecast, the associated stock price, and the EPS realization for the target year must be available from I/B/E/S. We also require sales (our proxy for size) from Compustat for the year immediately preceding the forecast.[11] Because losses are less persistent than positive earnings (Hayn 1995), we require positive earnings in the base year.[12] In sensitivity analyses, we find that including loss firms does not change our

[9] Untabulated statistics reveal that a hypothetical data requirement of 10 years of prior earnings data (e.g., Fried and Givoly 1982) would eliminate more than 60 percent of the observations, so estimating more complex time-series forecasts would result in a considerable loss of sample observations, and hence generalizability.

[10] When analysts forecast no change in EPS, the RW forecast and the analysts' forecasts are equal; thus, analysts' forecasts differ most from RW forecasts when analysts forecast large changes in EPS.

[11] For analyses that can be done without Compustat data (i.e., the main results and analyses related to firm age and the number of analysts following), the Compustat restriction makes no substantive difference in the results. However, we impose this restriction across all analyses to facilitate sample consistency across tables.

[12] The base year is the year from which we obtain data for RW forecasts. For example, when forecasting 1-year-ahead earnings (EPS_{T+1}), the base year is year T; when forecasting two-year-ahead earnings (EPS_{T+2}), the base year is still year T, etc.

overall conclusions.[13] Finally, we perform a number of additional market-based tests, which require sufficient monthly data from CRSP to calculate returns over the specified holding periods. This slightly reduces the sample for these tests.

For each target firm-years' earnings (EPS_{T+t}), we collect the I/B/E/S consensus analysts' forecast made in each of the previous 36 months. Thus, for the first 12 months prior to the earnings announcement, we use FY1 (the 1-year-ahead earnings forecast) as the analysts' earnings forecast and the EPS 1 year prior (EPS_T) as the RW forecast. For example, for 1-year-ahead earnings forecasts, we have 12 pairs of forecast errors across the 12 months prior to the announcement of actual earnings.[14] For each pair, the analysts' forecast error is the difference between the analysts' forecast (for example, Forecasted EPS_{T+1}) and realized earnings (for example, EPS_{T+1}), and the RW forecast error is the difference between EPS_T (that is, the RW forecast for $T + 1$) and EPS_{T+1}. We then take the absolute value of the forecast errors and scale by price as of the analysts' forecast date. We obtain 844,643 consensus forecasts, representing 77,013 firm-years and 10,919 firms, with sufficient data for the 1-year-ahead (FY1) analyses.

For the 12 through 23 months prior to the target year's earnings announcement date, we use I/B/E/S forecasts of FY2 (the 2-year-ahead earnings forecast). As with the forecasts of FY1, there are 12 monthly forecasts of FY2. For these months, the RW forecast of earnings for EPS_{T+2} is equal to EPS_T. We obtain 715,730 consensus forecasts, representing 68,870 firm-years and 9, 870 firms, with sufficient data for the 2-year-ahead (FY2) analyses.

Finally, for the 24 through 35 months prior to the target year's earnings announcement date, we construct estimates of FY3 (the 3-year-ahead earnings forecast) because few analysts forecast 3-year-ahead earnings directly. We construct these estimates using the method outlined in studies like Frankel and Lee (1998), Lee et al. (1999), Gebhardt et al. (2001), and Ali et al. (2003). This method generates the FY3 forecast from the FY2 forecast adjusted by the mean analysts' long-term growth forecast as follows:

$$\mathrm{FY3} = \mathrm{FY2} \times (1 + \mathrm{LTG\%}) \tag{1}$$

where FY2 is defined above, and LTG is the long-term growth forecast from I/B/E/S. To be in the FY3 sample, a firm must report positive base year earnings (EPS_T relative to EPS_{T+3}) and have a FY2 and long-term growth forecast in I/B/E/S.[15] We next calculate the pairs of forecast errors, analogous to the FY1 and FY2 analyses. We obtain 545,354 I/B/E/S consensus forecasts, representing 53,561 firm-years and 7,636 firms, with sufficient data for the 3-year-ahead (FY3) analyses.

[13] In unreported analyses, we find that including loss firms does not change the results over horizons of 1 year or less, the RW results improve somewhat relative to analysts' forecasts for forecast horizons of 2 and 3 years when loss firms are included.

[14] Note that when the earnings announcement is made early in the calendar month, there will not be an earnings forecast in that calendar month. For these observations, there are only forecasts of FY1. Thus, there are approximately half as many month 0 observations as there are month 1 observations.

[15] Using explicit FY3 forecasts when available in I/B/E/S, we find that our general conclusions are unchanged.

Our primary RW-based forecasts are simply the lagged annual realized earnings:

$$\mathrm{E_T(EPS_{T+\tau}) = EPS_T} \in \tau = \{1, 2, 3\} \tag{2}$$

Thus, for FY1 forecasts, the RW forecast is the realized EPS from the previous fiscal year, and for FY2 (FY3), the RW forecast is the realized EPS two (three) years prior to the forecast year.

The selection of which earnings figure to use as the basis of our random walk and analyst forecasts is based on our objective of providing benchmark evidence using the most obvious measures, rather than attempting to refine individual forecasts. For example, it is well known that various components of earnings exhibit differential persistence (for example, Lipe 1986; Elliott and Hanna 1996; Sloan 1996), so we could attempt to clean up historical earnings for special items not already excluded or construct an optimal weighting of income statement line items or components of accruals and cash flows.[16] Similarly, it is also well known that analyst forecast errors contain predictable components (for example, Abarbanell and Bernard 2000; Bradshaw et al. 2001), so we could also attempt to clean up analyst forecasts for predictable errors along the lines of approaches taken by Ali et al. (1992) and Frankel and Lee (1998). Both Bradshaw and Sloan (2002) and Abarbanell and Lehavy (2003) provide evidence that analysts and/or forecast data providers (like I/B/E/S) extensively purge transitory components from analyst forecasts. Thus, any attempt to purge noise, transitory components, or predictable errors from historical earnings or analyst forecasts would differentially benefit our random walk forecasts. Given our objective of determining whether the belief that analysts' forecasts are superior to simple extrapolations of earnings is empirically supported, we rely on unadjusted data.

4 Results

4.1 Descriptive statistics

Table 2 Panel A presents descriptive statistics for the 68,870 firm-years with sufficient data to estimate RW and analysts' forecast errors 11 months prior to the target earnings announcement. The mean (median) observation has only 7.6 (5) analysts following the firm, consistent with a large number of the firms in our sample having relatively sparse analyst coverage.

Panel B examines the signed forecast errors scaled by price for both types of forecasts at 11, 23, and 35 months prior to the earnings announcement date. The absolute magnitudes of the bias for the median forecast errors are similar, but the median RW forecasts are negatively biased (because EPS tends to grow by approximately 50 basis points per year), while the median analysts' forecast errors are positively biased (as in Richardson et al. 2004).

[16] Additionally, some researchers use cross-sectional models to derive earnings forecasts for individual firms (e.g., Fama and French 2006; Hou et al. 2010). These approaches are beyond the scope of our current analysis, but they could be combined with those discussed above to provide evidence on the extent to which researchers (or investors) could construct superior forecasts based on historical financial statements.

Table 2 Descriptive statistics

	Mean	Median	Q1	Q3
Panel A: Firm characteristics[a]				
Sales	2,921	410	125	1,504
BTM	0.5823	0.4985	0.3124	0.7391
Age	8.9340	7	3	13
# Analysts	7.5832	5	2	10
Panel B: Signed forecast errors[b]				
Signed random walk (RW) errors				
11 Months	0.0020	−0.0052	−0.0156	0.0131
23 Months	−0.0050	−0.0082	−0.0260	0.0180
35 Months	−0.0013	−0.0108	−0.0357	0.0204
Signed analysts' forecasts errors				
11 Months	0.0214	0.0030	−0.0043	0.0224
23 Months	0.0308	0.0104	−0.0044	0.0422
35 Months	0.0359	0.0173	−0.0041	0.0553

[a] The sample consists of all firms with data available 11 months prior to the earnings announcement date. Sales are in $ millions. Book-to-Market (BTM) and Sales are measured as of the end of the base year. Age is measured as the number of prior years for which I/B/E/S has recorded annual EPS for the firm. # Analysts is the number of analysts following measured as NUMEST for the statistical period 11 months prior to the report date of annual earnings

[b] Forecast errors are measured as the difference between forecasted and actual earnings scaled by price 11, 23, or 35 months prior to the earnings announcement

4.2 Tests of analysts' superiority using absolute forecast errors

Table 3 compares the forecast accuracy of RW forecasts based on annual EPS to that of the analysts' consensus forecasts for the full sample. We calculate the analysts' superiority over the RW model as follows (firm subscripts omitted):

$$\text{Analysts' superiority} = \frac{|\mathrm{EPS_T} - \mathrm{EPS_{T+\tau}}| - \left|\text{Forecasted } \mathrm{EPS_{T+\tau,M}} - \mathrm{EPS_{T+\tau}}\right|}{\mathrm{Price_{T,M}}} \in \tau = \{1,2,3\} \tag{3}$$

where Forecasted EPS is the consensus analysts' forecast (that is, FY1, FY2, or FY3) issued M months prior to the earnings announcement for year $T + \tau$ earnings. At each forecast horizon, we calculate mean Analysts' Superiority. A positive (negative) mean indicates that analysts are superior to (inferior to) a RW model at that particular forecast horizon, on average.[17]

The columns labeled FY1 present the mean analysts' superiority from 0 through 11 months prior to the earnings announcement. For the full sample, our results

[17] The measurement of analysts' forecast superiority requires matched pairs of RW and analysts' forecasts, so each observation requires a RW forecast, a consensus analysts' forecast, and the reported actual earnings.

Table 3 Results for analysts' forecast superiority, full sample

Forecasts of year T + 1			Forecasts of year T + 2			Forecasts of year T + 3		
Months prior	Firm-years	FY1 FE minus RW FE	Months prior	Firm-years	FY2 FE minus RW FE	Months prior	Firm-years	FY3 FE minus RW FE
0	36,688	0.0282	12	33,822	0.0134	24	25,418	0.0066
1	73,618	0.0267	13	63,869	0.0118	25	48,196	0.0050
2	73,791	0.0255	14	65,413	0.0105	26	49,347	0.0040
3	73,853	0.0237	15	65,660	0.0089	27	49,452	0.0031
4	73,953	0.0201	16	65,415	0.0066	28	49,293	0.0018
5	74,006	0.0172	17	65,059	0.0050	29	49,167	0.0007
6	74,030	0.0147	18	64,362	0.0038	30	48,769	(0.0000)^{NS}
7	73,935	0.0117	19	63,185	0.0023	31	48,083	(0.0012)
8	73,759	0.0095	20	61,837	0.0013	32	47,301	(0.0019)
9	73,505	0.0076	21	59,738	0.0003	33	46,096	(0.0026)
10	72,630	0.0051	22	56,207	(0.0007)	34	43,869	(0.0035)
11	70,875	0.0035	23	51,163	(0.0014)	35	40,363	(0.0041)

This table reports the mean difference between absolute analysts' forecast errors (FY1 FE, FY2 FE, and FY3 FE in years T + 1, T + 2, and T + 3 respectively) and absolute random walk forecast errors (RW FE) and in the 36 months prior to an earnings announcement. Negative numbers indicate random walk superiority. All errors are scaled by price at the time the analysts' forecast is made and are winsorized at 1. Year T is the year of the most recently reported annual earnings. Forecast error (FE) is the absolute value of the difference between the estimated and realized earnings scaled by price as of the forecast date. The three forecasts, FY1, FY2, and FY3, are measured as the analysts' consensus forecast of EPS for years T + 1, T + 2, and T + 3, respectively. The random walk (RW) forecast is equal to the most recently reported annual EPS. *NS* indicates not significant at the 10 percent level, using a two-tailed test. All other values are significantly different from zero (almost all at $p < 0.01$)

confirm those in the prior literature—analysts' forecasts *are* more accurate than forecasts from time-series models (specifically, forecasts from a RW model), and their superiority is more evident as the earnings announcement approaches. For forecasts made in the same month as the earnings announcement (that is, 0 months prior), analysts' forecasts are more accurate than RW forecasts by 282 basis points. In contrast, 11 months prior, analysts' superiority is only 35 basis points, which is approximately 88 percent smaller than analysts' superiority in month 0.

The columns labeled FY2 present the mean analysts' superiority from 12 through 23 months prior to the earnings announcement. Again, analysts' forecasts are significantly more accurate than RW forecasts from 12 through 21 months prior, but as with FY1, their relative superiority falls monotonically as the forecast horizon lengthens. Moreover, at month 21, analysts' superiority is only 3 basis points, and by months 22 and 23, the RW forecast is significantly more accurate than analysts' forecasts on average. However, the difference in accuracy is economically trivial, at 7 and 14 basis points respectively. The set of columns labeled FY3 presents the mean analysts' superiority from 24 through 35 months prior. Again, analysts' superiority falls monotonically, from 66 basis points at 24 months prior to −41 basis points at 35 months prior, as their timing and information advantages increase.[18]

Our evidence that simple RW forecasts dominate analysts' longer-term forecasts is consistent with intuition and evidence in prior literature. First, analysts may expend greater effort to forecast near-term earnings but may focus on more persistent (and likely higher) measures of earnings over longer horizons (Mest and Plummer 1999). Second, whereas near-term earnings are settled up in a timely manner and tracked by investors and ranking services, longer-term forecasts are less likely to be explicitly tracked (Stickel 1992). Third, due to various conflicts of interest (such as investment banking pressures, currying favor with management, and general optimism), analysts' long-term forecasts tend to exhibit much greater optimistic bias than do near-term forecasts (for example, Francis and Philbrick 1993).[19] Finally, given the stronger impact long-term forecasts have on valuations, all of the above effects converge to induce analysts to optimistically bias longer-term forecasts, which then support elevated valuations (that is, target prices) and optimistic stock recommendations.

4.2.1 Using analysts' forecasts of 1-year-ahead earnings to predict long-term earnings

The above analyses confirm that, as suggested in prior literature, over horizons of less than 1 year, analysts' forecasts clearly dominate RW forecasts. However, as the forecast horizon extends, RW forecasts begin to dominate analyst forecasts. These results suggest that using analysts' forecasts of 1-year-ahead earnings (FY1) in lieu of analysts' forecasts of 2- and 3-year-ahead earnings (FY2 and FY3) could yield more accurate forecasts of long-term earnings. Thus, we use FY1 as the earnings forecast for years $T + 2$ and $T + 3$, which is essentially a naïve random walk extrapolation of analysts' near-term earnings forecasts, and we label this new forecast the "short-horizon" analyst forecast.[20]

In Table 4, we compare the accuracy of the short-horizon analyst forecast with that of analysts' forecasts of 2- and 3-year-ahead earnings (FY2 and FY3, respectively) and with that of the RW forecast. In the left set of columns, the forecast target is year $T + 2$.[21] In columns (1) through (3), we present the mean

[18] In an additional test, we regress stock returns measured from the month of the forecast through the month of the earnings announcement separately on forecast errors from RW and analysts' FY1, FY2, and FY3 forecasts (as appropriate) using a seemingly unrelated regression system. We estimate this system for each of the 36 forecast horizons from 0 to 35 months prior to the earnings announcement and find that the relative weights that the market seems to assign to RW and analyst forecasts track fairly closely to the results of the accuracy tests in Table 3. Thus, we find that security prices generally reflect the more accurate forecast at each forecasting horizon.

[19] For example, in an examination of differential forecast optimism by affiliated analysts, Lin and McNichols (1998) find no differences for near-term earnings (i.e., forecasts with horizons of up to 2 years) but find both general and differential optimism for long-term growth forecasts.

[20] We thank Richard Sloan for suggesting that we investigate this alternative forecast.

[21] We do not tabulate the results for target year $T + 1$ because, for that horizon, there is no difference between the SH forecast error and the 1-year-ahead analyst forecast error (FY1), and those results on already tabulated in the first set of columns in Table 3.

Table 4 Relative accuracy of analysts' FY1 forecasts (SH), random walk, and analysts' explicit forecast for years T + 2 and T + 3, full sample

Forecasts of year T + 2					Forecasts of year T + 3				
Months prior	Number of firms	(1) FY2 FE minus SH FE	(2) RW FE minus SH FE	(3) RW FE minus FY2 FE	Months prior	Number of firms	(4) FY3 FE minus SH FE	(5) RW FE minus SH FE	(6) RW FE minus FY3 FE
13	63,699	(0.0006)	0.0112	0.0118	25	48,152	0.0005	0.0054	0.0050
15	65,533	0.0019	0.0108	0.0089	27	49,411	0.0028	0.0059	0.0031
17	64,957	0.0039	0.0089	0.0050	29	49,135	0.0049	0.0056	0.0007
19	63,117	0.0044	0.0066	0.0023	31	48,066	0.0059	0.0047	(0.0012)
21	59,705	0.0044	0.0047	0.0003	33	46,090	0.0063	0.0037	(0.0026)
23	51,141	0.0043	0.0029	(0.0014)	35	40,359	0.0068	0.0027	(0.0041)

The table reports the mean difference between the absolute value of earnings forecast errors based on three forecasts of future earnings. FY2 FE and FY3 FE are the forecast errors in year T + 2 and T + 3 where the earnings forecast is the analysts' consensus forecast for years T + 2 and T + 3 respectively. SH FE is the forecast error in year T + 2 or T + 3 where the forecast is set equal to the analysts' consensus forecast of year T + 1 earnings. RW FE is the forecast error in year T + 2 or T + 3 based on the most recently reported (i.e., in year T) annual EPS. All errors are scaled by price at the time the analysts' forecast is made and are winsorized at 1. Year T is the year of the most recently reported annual earnings. *NS* indicates not significant at the 10 percent level, using a two-tailed test. All other values are significantly different from zero (almost all at $p < 0.01$)

differences between absolute forecast errors scaled by price for the short-horizon analyst forecast, FY2, and RW. In the right set of columns, we perform similar analyses, in columns (4) through (6), but the forecast target is year T + 3. We tabulate every other forecasting horizon for parsimony.

The results of these analyses are striking. The short-horizon analyst forecast provides the best EPS estimate at nearly every horizon. Specifically, the short-horizon analyst forecast is more accurate than FY2 in 5 of the 6 year T + 2 forecast horizons (column (1)) and is more accurate than FY3 in all 6 year T + 3 forecast horizons (column (4)). In addition, the short-horizon analyst forecast is more accurate than RW for all 12 year T + 2 and T + 3 forecast horizons (columns (2) and (4), respectively). These results, together with those in Table 3 (that analysts' FY1 forecasts dominate RW across all horizons in months 1 through 11), suggest that for settings in which the researcher is concerned with average forecast errors, analysts' 1-year-ahead forecasts (FY1) provide the best forecasts at all three horizons years (T + 1, T + 2, and T + 3). This finding is important because 1-year-ahead analyst forecasts (FY1) are available for many more firms than are 2- and 3-year-ahead analyst forecasts. Thus, this approach can dramatically increase the sample size in studies that use long-term forecasts of earnings.

In our next set of analyses, we investigate the accuracy of analysts' forecasts of 2- and 3-year-ahead earnings (FY2 and FY3, respectively) versus that of the short-horizon analyst forecast and the RW forecast for various subsamples. The subsamples that we investigate are from settings where (1) analyst forecasts are known to be poor, (2) analysts forecast increases versus decreases in earnings, and (3) analysts forecast small versus large absolute changes in earnings.

4.2.2 Subsample analysis

In Table 5, we investigate settings where analyst forecasts are generally poor–for young firms and for small firms.[22] Panel A compares forecast accuracy for young firms where we measure firm age using the number of years to date since the firm first reported positive assets on Compustat. Because samples in prior literature are comprised of mature firms (where analyst forecasts are more likely to dominate random walk), we focus our examination on young firms, defined as those less than 5 years old, to compare the relative accuracy of long-term forecasts. For young firms, we find that in all horizons, the short-horizon analyst forecast dominates both analysts' 2- and 3-year ahead forecasts (FY2 and FY3) and dominates RW (columns (1), (2), (4), and (5)). However, we also find that RW is as good as or better than FY2 in half (that is, three of six) of the forecasts horizons for year T + 2 earnings (column (3)) and that RW is as good as or better than FY3 in an all (that is, six of six) of the forecasts horizons for year T + 3 earnings (column (6)). The superiority of RW over analysts' explicit long-term forecasts is up to 83 basis points (at month 35).

Panel B compares forecast accuracy for small firms, defined as firms with sales that are less than the median sales in Compustat in the year. For small firms, we again find that the short-horizon analyst forecast dominates all other forecasts at every forecast horizon (columns (1), (2), (4), and (5)). We also find that RW is as good as or better than FY2 in 3 of 6 months (column (3)) and is as good as or better than FY3 in all months (column (6)). The superiority of RW over analysts' explicit long-term forecasts is up to 118 basis points (at month 35).

We draw the following general inferences from Table 5. First, in settings where analysts' long-term forecasts are generally thought to be less accurate, RW forecast are as good as analysts' explicit forecasts (FY2 and FY3) for horizons of more than 20 months. Second, we find that analysts' short-horizon forecasts dominate all other forecasts at *every* horizon.

4.2.3 The relation between analysts' superiority and the sign of the forecasted change in EPS

Table 6 partitions observations based on the sign of the analysts' forecasted change in EPS. In Panel A, we present the results for negative forecasted changes, and in Panel B, we present the results for positive forecasted changes. When comparing the accuracy of short-horizon forecasts with that of analysts' FY2 and FY3 forecasts and of RW, we find that short-horizon forecasts generally dominate for both forecasted decreases (columns (1), (2), (4), and (5) in Panel A) and forecasted

[22] In untabulated analyses, we also investigate thinly followed firms, defined as firms with four or fewer analysts forecasting 1-year-ahead earnings in I/B/E/S. We find that results are very similar to those for small firms.

Table 5 Relative accuracy of analysts' FY1 forecasts (SH), random walk, and analysts' explicit forecast for years T + 2 and T + 3, subsamples where analysts' forecasts of long-term earnings are known to be poor

Forecasts of year T + 2 earnings					Forecasts of year T + 3 earnings				
Months prior	Number of firms	(1) FY2 FE minus SH FE	(2) RW FE minus SH FE	(3) RW FE minus FY2 FE	Months prior	Number of firms	(4) FY3 FE minus SH FE	(5) RW FE minus SH FE	(6) RW FE minus FY3 FE
Panel A: Young firms (1–4 years old, based on the first year on Compustat)									
13	10,586	0.0008	0.0121	0.0113	25	7,290	0.0033	0.0060	0.0027
15	10,956	0.0039	0.0115	0.0076	27	7,593	0.0058	0.0055	(0.0003)[NS]
17	10,818	0.0060	0.0090	0.0031	29	7,553	0.0080	0.0051	(0.0029)
19	10,449	0.0063	0.0063	(0.0000)[NS]	31	7,346	0.0096	0.0044	(0.0052)
21	9,735	0.0063	0.0041	(0.0022)	33	6,921	0.0098	0.0033	(0.0066)
23	7,975	0.0059	0.0023	(0.0036)	35	5,787	0.0101	0.0018	(0.0083)
Panel B: Small firms (sales less than the Compustat median sales in the year)									
13	8,302	0.0017	0.0100	0.0083	25	4,469	0.0054	0.0038	(0.0016)
15	8,494	0.0045	0.0099	0.0054	27	4,649	0.0080	0.0043	(0.0037)
17	8,280	0.0071	0.0082	0.001	29	4,593	0.0102	0.0042	(0.0060)
19	7,832	0.0075	0.0055	(0.0020)	31	4,361	0.0117	0.0035	(0.0082)
21	7,119	0.0077	0.0038	(0.0040)	33	4,028	0.0121	0.0026	(0.0096)
23	5,512	0.0076	0.0016	(0.0060)	35	3,244	0.0129	0.0011	(0.0118)

The table reports the mean difference between the absolute value of earnings forecast errors based on three forecasts of future earnings. FY2 FE and FY3 FE are the forecast errors in year T + 2 and T + 3 where the earnings forecast is the analysts' consensus forecast for years T + 2 and T + 3 respectively. SH FE is the forecast error in year T + 2 or T + 3 where the forecast is set equal to the analysts' consensus forecast of year T + 1 earnings. RW FE is the forecast error in year T + 2 or T + 3 based on the most recently reported (i.e., in year T) annual EPS. All errors are scaled by price at the time the analysts' forecast is made and are winsorized at 1. Year T is the year of the most recently reported annual earnings. *NS* indicates not significant at the 10 percent level, using a two-tailed test. All other values are significantly different from zero (almost all at $p < 0.01$)

Table 6 Relative accuracy of analysts' FY1 forecasts (SH), random walk, and analysts' explicit forecast for years T + 2 and T + 3, by the direction of analysts' forecasts

Forecasts of year T + 2 earnings					Forecasts of year T + 3 earnings				
Months prior	Number of firms	(1) FY2 FE minus SH FE	(2) RW FE minus SH FE	(3) RW FE minus FY2 FE	Months prior	Number of firms	(4) FY3 FE minus SH FE	(5) RW FE minus SH FE	(6) RW FE minus FY3 FE
Panel A: Forecasted decreases									
13	13,176	(0.0023)	0.0359	0.0382	25	5,727	(0.0038)	0.0214	0.0252
15	11,672	0.0025	0.0395	0.0370	27	5,022	0.0011	0.0269	0.0257
17	9,060	0.0070	0.0377	0.0307	29	3,839	0.0051	0.0288	0.0237
19	6,889	0.0063	0.0323	0.0260	31	2,788	0.0075	0.0283	0.0209
21	5,400	0.0041	0.0250	0.0209	33	2,195	0.0049	0.0230	0.0181
23	3,760	0.0026	0.0199	0.0173	35	1,564	0.0027	0.0175	0.0148
Panel B: Forecasted increases									
13	50,523	(0.0001)^{NS}	0.0048	0.0049	25	42,425	0.0011	0.0033	0.0022
15	53,861	0.0018	0.0046	0.0029	27	44,389	0.0030	0.0035	0.0005
17	55,897	0.0034	0.0042	0.0008	29	45,296	0.0049	0.0036	(0.0013)
19	56,228	0.0042	0.0035	(0.0007)	31	45,278	0.0058	0.0032	(0.0026)
21	54,305	0.0044	0.0027	(0.0017)	33	43,895	0.0064	0.0028	(0.0036)
23	47,381	0.0044	0.0015	(0.0029)	35	38,795	0.0069	0.0021	(0.0048)

The table reports the mean difference between the absolute value of earnings forecast errors based on three forecasts of future earnings. FY2 FE and FY3 FE are the forecast errors in year T + 2 and T + 3 where the earnings forecast is the analysts' consensus forecast for years T + 2 and T + 3 respectively. SH FE is the forecast error in year T + 2 or T + 3 where the forecast is set equal to the analysts' consensus forecast of year T + 1 earnings. RW FE is the forecast error in year T + 2 or T + 3 based on the most recently reported (i.e., in year T) annual EPS. All errors are scaled by price at the time the analysts' forecast is made and are winsorized at 1. Year T is the year of the most recently reported annual earnings. *NS* indicates not significant at the 10 percent level, using a two-tailed test. All other values are significantly different from zero (almost all at $p < 0.01$)

increases (columns (1), (2), (4), and (5) in Panel B). However, when comparing analysts' FY2 and FY3 forecasts with RW, we find that explicit forecasts of FY2 and FY3 always dominate RW when analysts forecast negative EPS changes (columns (3) and (6) in Panel A). Thus, we find that, although analysts forecast negative earnings changes less often than they forecast positive earnings changes, when they do, analysts' superiority over RW is stronger. That said, the small number of negative forecasted changes in FY3 reveals that analysts very rarely forecast negative changes in 3-year-ahead earnings (that is, approximately 1 in 1,000 forecasted changes are negative over these horizons). When analysts forecasts positive earnings changes (Panel B), we find that RW forecasts are as good as FY2 in 3 of 6 months (column (3)) and are as good as FY3 in 4 of 6 months (column (6)).

4.2.4 The relation between analysts' superiority and the magnitude of the forecasted change in EPS

Table 7 partitions observations based on the magnitude of the analysts' forecasted change in EPS. In Panel A, we present the smallest trecile of forecasted changes in earnings, and in Panel B, we present the largest trecile of forecasted changes in earnings. When comparing the accuracy of short-horizon forecasts with that of analysts' FY2 forecasts (column (1)), we find that short-horizon forecasts generally dominate for both small (Panel A) and large (Panel B) forecasted changes. However, the results reveal a stark difference in short-horizon forecast dominance for forecasts of year $T + 3$ earnings. For small forecasted changes, we find that FY3 dominates short-horizon forecasts (column (4) in Panel A) but for large forecasted changes, we find that short-horizon forecasts dominate FY3 (column (4) in Panel B). Thus, when analysts forecast larger year $T + 3$ deviations from current earnings, the short-horizon forecast provides a more accurate forecast than does FY3.

When comparing the accuracy of the RW forecast with that of analysts' FY2 forecasts, we find that analyst forecasts always dominate RW when they forecast small changes in earnings (columns (3) and (6) in Panel A). However, when analysts forecast large changes in earnings, RW dominates FY2 in 2 of 6 months (column (3) in Panel B) and RW is as good as FY3 in 5 of 6 months (column (6) in Panel B).

5 Conclusion

We show that the widely held belief that analysts' forecasts of annual earnings are superior to time-series forecasts is not fully descriptive. Although analysts' earnings forecasts consistently beat RW earnings forecasts over short windows, for longer forecast horizons, analysts' superiority declines, and at certain horizons, analysts' forecasts are dominated by RW forecasts. This is especially true for small firms, for young firms, and when analysts forecast positive or more extreme changes in earnings. In addition, we run a horse race between three estimates of long-term (that is, 2- and 3-year-ahead) earnings—analysts' explicit forecasts, analysts' short-horizon (1-year-ahead) forecasts, and RW forecasts. We find that the short-horizon

Table 7 Relative accuracy of analysts' FY1 forecasts (SH), random walk, and analysts' explicit forecast for years T + 2 and T + 3, by the magnitude of the absolute forecasted change in earnings

Forecasts of year T + 2 earnings					Forecasts of year T + 3 earnings				
Months prior	Number of firms	(1) FY2 FE minus SH FE	(2) RW FE minus SH FE	(3) RW FE minus FY2 FE	Months prior	Number of firms	(4) FY2 FE minus SH FE	(5) RW FE minus SH FE	(6) RW FE minus FY2 FE
Panel A: Small forecasted change (smallest 1/3 of forecasted changes)									
13	22,920	(0.0005)	0.0033	0.0038	25	17,982	(0.0029)	0.0023	0.0052
15	23,165	0.0015	0.0047	0.0032	27	17,785	(0.0013)	0.0037	0.0050
17	22,041	0.0027	0.0056	0.0028	29	16,614	(0.0002)^{NS}	0.0049	0.0051
19	20,560	0.0023	0.0050	0.0027	31	15,381	(0.0006)	0.0050	0.0056
21	18,519	0.0017	0.0044	0.0027	33	13,976	(0.0010)	0.0048	0.0057
23	14,874	0.0008	0.0035	0.0027	35	11,446	(0.0021)	0.0042	0.0062
Panel B: Large forecasted change (largest 1/3 of forecasted changes)									
13	20,578	(0.0006)^{NS}	0.0231	0.0237	25	14,697	0.0047	0.0090	0.0043
15	21,248	0.0030	0.0202	0.0172	27	15,495	0.0081	0.0083	0.0002^{NS}
17	21,468	0.0062	0.0143	0.0081	29	16,118	0.0115	0.0066	(0.0049)
19	21,100	0.0074	0.0094	0.0020	31	16,422	0.0134	0.0042	(0.0091)
21	20,405	0.0080	0.0055	(0.0025)	33	16,389	0.0144	0.0026	(0.0117)
23	18,138	0.0087	0.0025	(0.0061)	35	15,092	0.0156	0.0010	(0.0147)

The table reports the mean difference between the absolute value of earnings forecast errors based on three forecasts of future earnings. FY2 FE and FY3 FE are the forecast errors in year T + 2 and T + 3 where the earnings forecast is the analysts' consensus forecast for years T + 2 and T + 3 respectively. SH FE is the forecast error in year T + 2 or T + 3 where the forecast is set equal to the analysts' consensus forecast of year T + 1 earnings. RW FE is the forecast error in year T + 2 or T + 3 based on the most recently reported (i.e., in year T) annual EPS. All errors are scaled by price at the time the analysts' forecast is made and are winsorized at 1. Year T is the year of the most recently reported annual earnings. *NS* indicates not significant at the 10 percent level, using a two-tailed test. All other values are significantly different from zero (almost all at $p < 0.01$)

forecast dominates analysts' explicit forecast of long-term earnings and dominates a RW forecast for almost every horizon and subsample we examine.

While our results are not inconsistent with prior literature that concludes that analysts' forecasts are superior to forecasts from time-series models in a general sense, we find that over longer horizons, analysts' explicit long-term forecasts lose their relative superiority to time-series forecasts. In fact, even a simple RW forecast performs as well, in both an economic and statistical sense, relative to analysts' forecasts. Moreover, analysts' short-horizon forecasts dominate both RW and analysts' explicit long-term forecasts. This is important because analysts' long-term forecasts are not available for a large number of firms. Our findings suggest that investors can reasonably rely on analysts' short-horizon forecasts or on RW forecasts when implementing long-term buy-and-hold valuation strategies (where cross-sectional averages are the focus), and similarly, researchers interested in phenomena that require longer-term earnings expectations can work with larger samples than those comprised of firms with long-term analysts' forecasts. Finally, our finding that RW forecasts (and naïve extrapolation of analysts' short-horizon forecasts) are more accurate than analysts' explicit forecasts over long horizons implies that these alternative forecasts would improve prediction models of firm-specific valuation estimates, cost of capital, or stock returns. We leave these issues for future research.

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