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

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Abstract: In this paper, we re-examine the widely-held belief that analysts' earnings per share (EPS) forecasts are superior to forecasts from a time-series model. Using a naive random walk time-series model for annual earnings, we investigate whether and when analysts' annual forecasts are superior. We also examine whether analysts' forecasts approximate market expectations better than expectations from a simple random walk model. Our results indicate that simple random walk EPS forecasts are more accurate than analysts' forecasts over longer forecast horizons and for firms that are smaller, younger, or have limited analyst following. Analysts' superiority is less prevalent when analysts forecast large changes in EPS. These findings suggest an incomplete and misleading generalization about the superiority of analysts' forecasts over even simple time-series-based earnings forecasts. Our findings imply that in certain settings, researchers can reliably use time-series-based forecasts in studies requiring earnings expectations.

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1. Introduction

Research on analysts' forecasts originated from a need within capital markets research to find a reliable proxy for investor expectations of earnings per share (EPS). The need for a proxy was necessitated by a growing interest in the relation between accounting earnings and stock returns that began with Ball and Brown (1968). Prior to the widespread availability of analysts' forecasts, much capital markets research was aimed at better understanding the time-series properties of earnings in an effort to gauge the association between earnings expectations and stock prices (e.g., Ball and Watts 1972, Brooks and Buckmaster 1976, Albrecht et al. 1977, Salomon and Smith 1977, Watts and Leftwich 1977). Numerous time-series specifications are examined in these studies, but the overall evidence points towards sophisticated time-series models rarely providing an economically significant improvement over a simple random walk model in terms of reduced forecast errors. This led Brown (1993, 295) to observe that the general consensus among researchers is that earnings follow a random walk, which he states was "pretty much resolved by the late 1970s."

Between 1968 and 1987, numerous studies examined whether analysts are superior to time-series forecasts. The culmination of that research is Brown et al. (1987a), who conclude that analysts' forecasts are superior to time-series forecasts because of both an information advantage and a timing advantage. This conclusion led to a sharp decline in research on the properties of time-series forecasts. Indeed, in a review of the capital markets literature, Kothari (2001, 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 concluded that analysts' forecasts are superior to those from time-series models.

In this paper, we re-examine this widely-held belief that analysts' EPS forecasts are superior to those from time-series models. We do this by comparing the performance of simple random walk annual earnings forecasts to that of analysts' annual earnings forecasts, and by correlating the associated forecast errors with long-window market returns. Given information and timing advantages (Brown et al. 1987a), it seems improbable that analysts would not provide more accurate forecasts than a simple random walk model. However, the prior research upon which the conclusion that analysts are superior is based is subject to numerous caveats (e.g., small samples, bias towards large firms, small economic significance, etc.), as we discuss in detail below. Moreover, analysts are subject to a number of conflicting incentives that can result in biased or inaccurate forecasts (e.g., Francis and Philbrick 1993, Dugar and Nathan 1995, McNichols and O'Brien 1997, Lin and McNichols 1998).

As noted in Bradshaw (2009), the accounting literature is unique in its conclusion that expert forecasts are superior to forecasts from time-series models. For example, the economics literature is largely consistent with time-series models outperforming experts.[2] Obviously, forecasts of macroeconomic variables like interest rates, unemployment and GDP are different from forecasts of accounting earnings, because firm managers can affect both analysts' forecasts

[1] Kothari (2001, 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."

[2] For example, Belongia (1987) examines expert and time-series forecasts of interest rates, and finds that the time-series forecasts are more accurate. Similarly, Fintzen and Stekler (1999) and Loungani (2000) find that time-series forecasts of recessions and of gross domestic product (GDP) are more accurate than expert forecasts, respectively.

(through guidance) and accounting earnings (through financial reporting discretion) (Watts and Zimmerman 1990, Matsumoto 2002). This interaction clearly gives financial analysts' forecasts of EPS an advantage vis-à-vis expert forecasts of 'less controllable' economic outcomes like interest rates or GDP.

Furthermore, relative to the extensive amount of analyst forecast data currently available, the empirical results of the early studies examining analysts versus time-series models are based on very small samples. 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. In addition to the limited availability of machine readable data when these studies were performed, another explanation for the small sample sizes is the data demands of ARIMA models, which require a long time series of earnings (e.g., 10 to 20 years) to estimate time-series parameters. Other common research design choices, such as the selection of only December fiscal year-end firms or only firms trading on the New York Stock Exchange (which bias samples towards large, mature, and stable firms), may also affect early results. Finally, the firms followed by analysts are biased towards larger firms with institutional following (Bhushan 1989) and with more extensive disclosures (Lang and Lundholm 1996), which censors the availability of analysts' forecasts for other firms. The generalizability of the early evidence on analysts' forecast superiority is accordingly limited, as is made clear by descriptions in these studies about sample characteristics and by other caveats.

Researchers frequently use analysts' forecasts as a proxy for expected earnings for samples 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 underrepresented in the early studies on the accuracy of analysts' versus time-series forecasts). Similarly, researchers use analysts' forecasts of earnings over horizons which are not represented in these early studies (which rarely examine forecast horizons beyond one year). For example, in the valuation and cost of capital literature (e.g., Frankel and Lee 1998; Claus and Thomas 2001; Gebhardt et al. 2001; Easton et al. 2002; and Hribar and Jenkins 2004), analysts' earnings forecasts are often used as a proxy for longer-horizon earnings expectations, such as two- to five-year-ahead earnings. One notable exception is Allee (2008) who utilizes exponential smoothing time-series forecasts for two-year horizons to estimate the firm-specific 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 recommends that researchers and investors use time-series forecasts of earnings to estimate the implied cost of equity capital for firms not covered by analysts.

Our empirical tests are based on annual earnings with forecast horizons ranging from 1 month to 36 months. We focus solely on annual 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 random walk forecasts are superior to analysts' forecasts in the quarterly setting, where both the information and timing advantage of analysts are greatest.[3] Our focus on annual earnings forecasts is also consistent with the extensive use of these forecasts in research on the

[3] We do not directly examine this conjecture, but our near-term forecasts of annual earnings are analogous to quarterly forecasts for the fourth quarter and for these very short forecasting horizons, the results are consistent with analysts dominating time-series models.

cost of equity capital and valuation, where longer horizon forecasts are the most cogent in terms of their influence on valuation-related estimates.

We document several surprising findings. First, for longer forecast horizons, analysts' forecasts do *not* consistently provide more accurate estimates of future earnings than time-series models, even when analysts have timing and information advantages. Second, for forecast horizons where analysts *are* more accurate than random walk forecasts (i.e., shorter forecast horizons of several months), the differences in forecast accuracy are economically small. Third, random walk forecasts are more accurate than analysts' forecasts for estimating two-year-ahead earnings in approximately half of the forecast horizons analyzed, and random walk forecasts strongly dominate analysts' forecasts of three-year-ahead earnings. Fourth, over longer forecast horizons, analysts' forecast superiority is prevalent in limited settings, such as for firms with small changes in EPS (consistent with analysts being superior to time-series models) in settings characterized by stable earnings). Finally, the associations between random walk versus analysts' forecast errors and stock returns track the results of the accuracy tests. Over the shortest forecast horizon, when analysts' forecasts and earnings announcements occur almost simultaneously, the association between analysts' forecast errors and returns is three times larger than that between random walk forecast errors and returns. However, over longer forecast horizons, returns are more strongly related to random walk forecast errors than to analysts' forecast errors, suggesting that random walk forecasts are a better proxy for market expectations of earnings than consensus analysts' forecasts over all but very limited forecast horizons.

These results conflict with common (often implicit) assertions that analysts' forecasts are uniformly a better proxy for investor expectations than are forecasts from time-series models. For example, Frankel and Lee (1998, 289) state that *I/B/E/S* earnings forecasts "should result in a more precise proxy for market expectations of earnings." They use these forecasts as a proxy for expected earnings for horizons of up to three years. Similarly, Easton et al. (2002) proxy for expected earnings using analysts' forecasts for horizons of up to four years, and Claus and Thomas (2001) use analysts' forecasts for horizons of up to five years. The evidence that time-series forecasts perform as well or better than analysts' forecasts suggests that the generalizability of research typically confined to firms for which analysts forecast long-term earnings (i.e., large, mature firms) may be reliably enhanced by substituting time-series forecasts for those of analysts and by expanding the samples of firms examined.

Although the tenor of our conclusions appears to contradict conclusions in early analysts' forecast research and questions the use of analysts' forecasts in more recent studies, we emphasize that early research was deliberate in its sample selection and other research design choices, and the conclusions were drawn appropriately. As in many literatures, it is the subsequent researcher who over-generalizes findings in the prior literature (Bamber et al. 2000). The early research examines the relative accuracy of time-series versus analysts' forecasts using samples of firms that were large, mature, and stable, and studied fairly limited forecast horizons. For these types of firms, over relatively short horizons, we also find that analysts' forecasts consistently outperform forecasts from a random walk model (and from all of the other time-series models that we evaluate).[4] However, we do emphasize that for all but the very shortest of

[4] In untabulated analyses, we also find that random walk forecasts are superior to forecasts from more complicated time-series models such as random walk with a drift. This superiority exists for two reasons. First, analysts are better at estimating earnings for firms with sufficient data to calculate the time-series parameters in some complicated time-series models because longer time-series availability is associated with more mature firms.

forecast horizons, analysts' forecast superiority is economically small for the average firm. Moreover, for smaller firms and for firms with low analyst following, we find that analysts' superiority is quite small, and over longer horizons, analysts' forecasts are not superior to random walk forecasts.

The remainder of this paper proceeds as follows. In section 2, we review the prior literature. We describe our data and develop hypotheses in section 3. We present the results of our tests in section 4, and section 5 concludes.

2. Prior research and motivation

2.1 Prior Research

Numerous studies examine the time-series properties of annual earnings, motivated by a need for a well-specified expectations model to be used in asset pricing tests. The early studies (e.g., Little 1962, Ball and Watts 1972) provide evidence that annual earnings approximate a simple random walk process. Subsequent studies (e.g., Albrecht et al. 1977, Watts and Leftwich 1977) find that this simple time-series characterization performs at least as well as more complex models of annual earnings, such as random walk with drift or Box Jenkins.[5] Based on this evidence, Brown (1993, 295) concludes that earnings follow a random walk and that this was "pretty much resolved by the late 1970s." In addition to the empirical evidence, the random walk model is advantageous because it does not require a long time series of data, which restricts the sample size and induces survivor bias.

A stream of literature based on these prior studies compares the accuracy of earnings forecasts from time-series models to that of analysts' forecasts. These studies can be broadly classified into one of two lines of research. The first line asks whether analysts' forecasts *are superior to* forecasts derived from time-series models. These studies are motivated by the intuition that analysts' forecasts should be more accurate than time-series forecasts for a number of reasons (e.g., analysts have access to more information and have a timing advantage), and these studies provide evidence that analysts' forecasts are more accurate than time-series forecasts. For example, Fried and Givoly (1982) argue that analysts' superiority is related to 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 compare prediction errors (defined as (forecasted EPS – realized EPS) / |realized EPS|) based on analysts' forecasts made approximately eight months prior to the fiscal-end date to those based on forecasts from two time-series models. The eight-month forecast horizon roughly corresponds to the annual forecast horizon of time-series models based on earnings releases, which typically occur by four months after fiscal year-end. Fried and Givoly (1982) report prediction errors of 16.4 percent using analysts' forecasts versus 19.3 percent using a modified sub-martingale random walk model and 20.3 percent using a random walk model.[6] The

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Second, adding time-series parameters to a random walk forecast does not help much because the negative serial correlation in EPS changes is very small.

[5] Albrecht et al. (1977) also show that the choice of scalar is important to the relative accuracy of predictions from random walk versus random walk with drift models. Specifically, a random walk model outperforms a random walk with drift model when earnings are deflated by stockholders' equity but underperforms when earnings are not deflated.

[6] Fried and Givoly (1982) analyze a modified submartingale model that uses the firm's past earnings growth as the drift term as well as an index model that uses past earnings growth of the Standard & Poor's 500 as the drift term. Our focus is limited to the random walk model out of simplicity; refinement to incorporate past earnings growth

differences among these prediction errors seem small but are statistically significant. Fried and Givoly (1982) also find that analysts' forecast errors are more closely associated with security price movements than are forecast errors from time-series models. Collins and Hopwood (1980) document similar evidence using a slightly longer forecast horizon. Using forecasts made four quarters prior to year-end, they find mean analysts' forecast errors of 31.7 percent compared to 32.9 percent for their most accurate time-series forecast, again, an economically small but statistically significant difference.

A related line of research investigates the source of this apparent superiority. For example, Brown et al. (1987b) find that analysts' forecast superiority is positively (negatively) related to firm size (forecast dispersion). Similarly, Brown et al. (1987a) provide evidence consistent with analysts possessing an information advantage in that they better utilize information available on the date on which the time-series forecast is made, which Brown et al. (1987a) label a "contemporaneous advantage," and with analysts better utilizing information acquired between the date on which the time-series forecast is made and the date on which the analysts' forecast is made, which they label a "timing advantage." Subsequent research supports their conclusion that analysts' superiority is negatively associated with the forecast horizon (Kross et al. 1990; Lys and Soo 1995). 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*.

Collectively, these studies use samples comprised mainly of large firms. One exception is Branson et al. (1995) who re-examine the question of whether analysts' forecasts are superior to forecasts from time-series models using a sample of small market capitalization firms (where the median market value of equity is $215 million). Using one-quarter-ahead forecasts, they find that analysts' forecasts are also more accurate than time-series forecasts for their sample, but conclude that time-series models might be useful for small firms without analyst following. More recently, Allee (2008) examines cost of equity capital estimates based on time-series forecasts, so is able to extend his analyses to firms without analyst following. He uses two-year-ahead annual forecasts combined with the Easton (2004) implementation of the Ohlson and Jeuttner-Nauroth (2005) earnings growth valuation model to back-out the implied cost of equity capital. His results are also encouraging with respect to the usefulness of time-series forecasts in a valuation setting.

To succinctly summarize and place some structure on the prior research on analysts' versus time-series forecasts, table 1 summarizes twelve important studies on the relative performance of time-series and analysts' forecasts. We compile summary data on the sample size and time-period, the 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 by current capital markets research standards, ranging anywhere from only 50 to only a few hundred firms. Third, the time-series models used require a minimum of 10 years of data, and some require as many as 20 years of data. Fourth, the forecast horizons studied range from one quarter ahead in the quarterly setting to 18 months ahead in the annual setting, with the

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would likely improve the performance of time-series forecasts relative to analysts' forecasts, but would require longer time series, thus biasing the sample.

majority focused on the quarterly forecast horizon. Fifth, forecast accuracy is generally evaluated using the absolute value of forecast errors scaled by either actual EPS or stock prices. Sixth, the reported differences in forecast accuracy between analysts and time-series models are typically statistically significant and analysts typically 'win,' but the economic magnitudes of the differences appear modest at best. Finally, analysts' forecast advantage is positively associated with firm size and is 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?

Two factors, combined with the availability of analysts' forecasts for a large number of public firms, motivate our re-examination of the superiority of analysts' forecasts over time-series forecasts. First, our review of the accounting and finance literature above suggests that it took approximately two decades (i.e., the 1970s and 1980s) 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, as noted above and as evident in table 1, this generalized conclusion is primarily based on studies investigating small samples of firms that are large, mature, and stable, and the margin of analysts' superiority over time-series forecasts is not overwhelming. However, analysts' forecasts are used pervasively in the literature as proxies for market expectations for all firms, both large and small. 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; her evidence indicates that market participants place more weight on time-series forecasts relative to analysts' forecasts as analyst following decreases. Additionally, it is not obvious that analysts are equally skilled at predicting earnings for large and small firms (or for firms that differ on other dimensions).

The second motivation for our re-examination is that a significant number of firms are not covered by analysts 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 firms to have available analysts' forecasts unnecessarily limits the data upon which this research is based and hence, is a costly restriction. To get a sense of the cost (in terms of sample exclusion) of requiring analysts' forecasts, we identify the number of firms with available financial and market data which is not included in *I/B/E/S*. In figures 1 and 2 respectively, we present plots of the number and percentage of public firms with available data in *Compustat* and in the Center for Research in Securities Prices (*CRSP*) that *do not* have analysts' one- and two-year-ahead earnings forecasts and long-term growth forecasts available in *I/B/E/S*.[8] As illustrated in figure 2, the percentage of firms with available *Compustat* and *CRSP* data that do not have a one-year-ahead analyst forecast data in *I/B/E/S* ranges from approximately 55 percent in 1980 to 25 percent in 2007. This trend generally decreases over time but we note a marked increase from 2000 to 2002 in the number of firms that are not covered, peaking in 2002

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[7] Since the 1980s, the forecasting literature has focused on refinements to better understand 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).

[8] We identify this sample by starting with all firms in *Compustat* with positive total assets. We retain all observations 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 is available for the remaining firms.

around the time of the Global Settlement. Figures 3 and 4 present plots of the mean and median assets of firms with available *Compustat* and *CRSP* data that are covered by analysts on *I/B/E/S*. As noted in prior research, the uncovered firms are considerably smaller (Bhushan 1989). Broadly, the evidence in figures 1 through 4 highlights the cost of requiring analysts' forecasts in terms of excluding otherwise useable data.

2.3 Empirical Methodology

In the first set of tests, we compare the accuracy of analysts' forecasts of annual earnings to that of time-series forecasts over various horizons ranging from 1 through 36 months prior to the earnings announcement date. Consistent with prior studies, we expect analysts' superiority to decrease as the forecast horizon increases (Brown et al. 1987a). Next, we investigate settings where we would expect analysts to have less of an information advantage. That is, we compare the forecast accuracy of analysts' forecasts to that of time-series models for young firms, small firms and for firms with low analyst following. We also examine how much information analysts add when they forecast large versus small changes in EPS by partitioning observations based on small, moderate, and large forecasted changes. When analysts forecast no change in EPS, the random walk forecast and the analysts' forecasts are equal; thus, analysts' forecasts differ most from random walk forecasts when analysts forecast large changes in EPS.

In the second set of tests, we examine the association between random walk forecast errors and stock returns, and the association between analysts' forecast errors and stock returns. Here, we also expect that the relative strength of the correlation between analysts' forecast errors and returns over the correlation between random walk forecast errors and returns to decrease as the forecast horizon increases and to be lower in settings where we expect analysts to have less of an advantage or when analysts forecast greater changes in future earnings.

As a final test, we investigate analysts' superiority in a multivariate setting. For each forecast horizon, we estimate regressions with our measure of analysts' superiority as the dependent variable and proxies for the quality of the information environment, firm risk, and the analysts' forecasted changes in earnings as covariates. The objective of this test is to investigate the incremental impact of these factors on analysts' superiority and to assess whether the impact changes across the various forecast horizons.

3. Data

We first collect data from the *I/B/E/S* consensus file and from the *Compustat* annual file. Our sample spans a 25 year period, from 1983 through 2007. We attempt to impose minimal constraints on data availability. For a firm-year observation to be included in our sample, the prior year's EPS, at least one earnings forecast and the associated stock price, and the EPS realization for the target year must be available from *I/B/E/S*. We also require that sales (our proxy for size) be available from *Compustat* for the year immediately preceding the forecast.[9] Because losses are less persistent than positive earnings (Hayn 1995), we further limit our

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

analyses to firm-years with positive earnings in the base year.[10] It is important to note that this research design choice favors random walk forecasts (but only slightly); however including loss firms does not change our overall conclusions.[11] Finally, for the market-based tests, we require sufficient monthly data from *CRSP* to calculate returns over the specified holding periods, which slightly reduces the sample for these tests.

For each target firm-years' earnings (EPS_T), we collect the *I/B/E/S* consensus analysts' forecast made in each of the previous 36 months. For the first 12 previous months (i.e., 0 through 11 months prior), we use FY1 (the one-year-ahead earnings forecast) as the measure of the analysts' forecast of earnings, and the EPS one year prior (EPS_{T-1}) as the random walk forecast of earnings. Thus, for the first year prior to the target year's earnings announcements, we have 12 pairs of forecast errors.[12] For each pair, the analysts' forecast error is the difference between the analysts' forecast and realized earnings (EPS_T) and the random walk forecast error is the difference between EPS_{T-1} and EPS_T. We then take the absolute value of the forecast errors and scale by price as of the analysts' forecast date. We obtain 740,070 consensus forecasts, representing 69,483 firm-years and 10,140 firms with sufficient data to be included in the one-year-ahead (FY1) analyses.

For the 12 through 23 months prior to the target year's earnings announcement date, we use the *I/B/E/S* forecasts of FY2 (the two-year-ahead earnings forecast). As with the forecast of FY1, there are 12 monthly forecasts of FY2. For these months, the random walk forecast of earnings is equal to EPS_{T-2}. We obtain 611,132 consensus forecasts, representing 60,170 firm-years and 9,037 firms with sufficient data to be included in the two-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 when necessary (the three-year-ahead earnings forecast) because very few analysts forecast three-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), which generates the FY3 forecast from the FY2 forecast adjusted by the mean analysts' long-term growth forecast as follows:

$$FY3 = FY2 \times (1 + LGT\%) \qquad (1)$$

where FY2 is defined above and LTG is the long-term growth forecast from *I/B/E/S*. Thus, to be included in the FY3 sample, a firm must report positive base year earnings (EPS_{T-3}), and have a FY2 forecast and a long-term growth forecast available in *I/B/E/S*. We next calculate the pairs of forecast errors, analogous to the FY1 and FY2 analyses. We obtain 468,777 *I/B/E/S* consensus forecasts, representing 46,226 firm-years and 7,070 firms with sufficient data to be included in the three-year-ahead (FY3) analyses.

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[10] The base year is defined as the year immediately preceding the forecast. For example, letting the target year be year T, when forecasting one-year-ahead earnings, the base year is year T-1; when forecasting two-year-ahead earnings, the base year is T-2; etcetera.

[11] In unreported analyses, we find that random walk forecasts perform poorly for fiscal periods following a loss; however, analysts' forecasts also perform poorly for these firms. While including loss firms does not change the results over horizons of one year or less, the random walk results improve somewhat relative to analysts' forecasts for forecast horizons of two and three years when loss firms are included. Although the lack of persistence of losses makes random walk a poor predictor of future earnings when the base years earnings are negative, analysts are aware of the base year's earnings before they make their forecasts, so this data restriction does not provide time-series models with a natural advantage.

[12] 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 11 forecasts of FY1. Thus, there are approximately half as many month 0 observations as there are month 1 observations.

As noted above, there is very little evidence suggesting that more sophisticated time-series models are more accurate than simple time-series models (Albrecht et al. 1977; Watts and Leftwich 1977; Brown et al. 1987a). Thus, our simple random walk-based forecasts of future earnings are simply the lagged realized earnings:

$$E_{T-\tau}(EPS_T) = EPS_{T-\tau} \ \in \tau > 0. \tag{2}$$

For FY1 forecasts, the random walk forecast is the realized EPS from the previous fiscal year, and for FY2 (FY3), the random walk forecast is the realized EPS two (three) years prior to the forecast year. Using the random walk forecast frees us from further data requirements that would skew our analyses to large, mature firms, as in prior research. Not surprisingly, we find a strong, positive association between firm age and the accuracy of both analysts' and random walk forecasts.

4. Results

4.1 Descriptive Statistics

Panel A of table 2 presents descriptive statistics for the 60,289 firm-years with sufficient data to estimate random walk forecast errors and analysts' forecast errors 11 months prior to the target earnings announcement. The mean (median) firm age is only 8 (4) years, so estimating more complex time-series forecasts would result in the loss of sample observations. For example, untabulated statistics reveal that a hypothetical data requirement of 10 years of prior earnings data (e.g., Fried and Givoly 1982) would eliminate 70 percent of the observations. We also find that the mean (median) observation has only 7.6 (5) analysts following, consistent with a large number of the firms in our sample having relatively sparse analyst coverage (i.e., only one or two analysts following).

As noted in table 1, prior literature frequently scales forecast errors by reported earnings and many important studies in this literature (e.g., Brown and Rozeff 1978; Fried and Givoly 1982; Brown et al. 1987a) winsorize forecast errors at 100 percent. For a sample comprised of large, mature firms and for forecasts with short horizons, this winsorization rule is reasonable because it results in very few of the analysts' forecast errors being winsorized. For example, Fried and Givoly (1982) find that approximately 0.5 percent of their sample observations have scaled forecast errors that are greater than 100 percent. Moreover, for the subsample of firms in our study that are at least 10 years old, we find that one month prior to the earnings announcement date, only 2.9 percent of scaled absolute analysts' forecast errors are greater than 100 percent. However, we find that for younger firms and over longer forecast horizons, many more extreme forecast errors exist. When we include younger firms in the analyses, the proportion of analysts' forecast errors (at the same forecast horizon) that are greater than 100 percent almost doubles (to 5.2 percent). Moreover, this proportion rises dramatically as the forecast horizon lengthens.

In panel B of table 2, we present the proportion of the absolute forecast errors (scaled by realized earnings) that are greater than 100 percent to illustrate the consequences of scaling forecast errors by reported earnings. For example, 35 months prior to the earnings announcement, almost 30 percent of analysts' forecast errors and 26 percent of random walk forecast errors are greater than 100 percent. Because winsorizing 30 percent of the sample could severely affect the reported results, in the analyses that follow, we scale forecast errors by price, as reported by *I/B/E/S*.[13] Scaling by price limits the number of extreme observations so that less than one percent of observations for both random walk forecast errors and analysts' forecast errors are greater than 100 percent at every forecast horizon. Thus, scaling by price provides a more accurate picture of the relative forecast accuracy of analysts versus random walk.

In panel C of table 2, we examine the bias in both types of forecasts. We report descriptive statistics for signed analysts' forecast errors and signed random walk forecast errors scaled by price at 11, 23, and 35 months prior to the earnings announcement date. We find that both forecast errors are biased, and that the absolute magnitudes of the bias for the median forecast errors are similar, but the biases are in the opposite direction. Specifically, the median random walk forecasts are negatively biased while the median analysts' forecast errors are positively biased. The negative bias in random walk forecast errors occurs because EPS tends to grow by approximately 50 basis points per year and the random walk model does not allow for this growth. Similarly, analysts' forecast errors are biased such that the median analysts' forecast error is consistently positive and is much larger at longer horizons. This pattern of bias in analysts' forecast errors is consistent with findings in Richardson et al. (2004).

4.2 Tests of Analysts' Superiority Using Absolute Forecast Errors

We present the main results of our tests in table 3. Here, we compare the forecast accuracy of random walk forecasts to that of the analysts' consensus forecasts for the full sample. We calculate the analysts' superiority as follows (firm subscripts omitted):

$$\text{Analysts' Superiority} = \frac{|EPS_{T-1} - EPS_T| - |Forecasted\ EPS_{T,M} - EPS_T|}{Price_{T,M}} \quad (3)$$

where *Forecasted EPS* is the analyst forecast (i.e., FY1, FY2, or FY3) issued M months prior to the earnings announcement for year T earnings. At each forecast horizon, we calculate mean Analysts' Superiority. A positive mean indicates that analysts are superior to a random walk model at that particular forecast horizon, on average, and a negative mean indicates that a random walk model is superior to analysts at that particular forecast horizon, on average.[14]

The first set of columns in table 3, labeled FY1, presents the mean analysts' superiority during months 0 through 11 prior to the earnings announcement. For the full sample, our results confirm those in the prior literature – analysts' forecasts *are* more accurate than forecasts from time-series models (specifically, forecasts from a random walk model) and their superiority is more evident as the earnings announcement approaches. For forecasts made in the same month as the earnings announcement (i.e., 0 months prior), analysts' forecasts are more accurate than random walk forecasts by 245 basis-points. This result is not surprising given that this is the forecast horizon where analysts have the greatest timing and information advantages. In other words, for most firms, the random walk forecast is approximately one year old at this time and analysts have the advantage of having access to all of the news that has occurred over the year and to the earnings announcements made in the first three quarters of the year (i.e., to three of the

[13] The price reported by *I/B/E/S* is usually the price at the end of the day prior to day on which the forecast is released. However, our results are insensitive to the measurement date for price. Specifically, our results are essentially unchanged when we scale by the first price for the fiscal year.

[14] Note that the measurement of analysts' forecast superiority requires matched pairs of random walk forecasts and analysts' forecasts. That is, for a given firm-year observation, we require both a random walk forecast (so a prior earnings realization) and a consensus analysts' forecast, as well as the reported earnings.

four quarterly earnings numbers used to calculate EPS_T). In contrast, 11 months prior to the earnings announcement date, analysts' superiority is only 25 basis-points, which is approximately 90 percent smaller than analysts' superiority in month 0.

The second set of columns, labeled FY2, presents the mean analysts' superiority from 12 through 23 months prior to the earnings announcement. Here, we use the consensus analysts' forecasts of two-year-ahead earnings and the random walk forecast is earnings reported two years prior to the target date. Again, analysts' forecasts are significantly more accurate than random walk forecasts from 12 through 21 months prior to the earnings announcement, but as with FY1, their relative superiority falls monotonically as the forecast horizon lengthens. Moreover, at month 21, analysts' superiority is only 4 basis-points, and by months 22 and 23, the random walk forecast is significantly more accurate than analysts' forecasts on average, so time-series forecasts are superior. However, the difference in accuracy is economically trivial, at 6 and 11 basis-points respectively.

The third set of columns, labeled FY3, presents the mean analysts' superiority from 24 through 35 months prior to the earnings announcement. Again, analysts' superiority falls monotonically, from 70 basis-points at 24 months prior to -40 basis-points at 35 months prior, as their timing and information advantages increase. Overall, table 3 reveals that, consistent with prior literature, analysts are better than time-series models at predicting earnings over relatively short windows. However, as the forecast horizon grows, analysts' superiority decreases and becomes negative, so that random walk forecasts are superior to analysts' forecasts, when the forecast horizon is sufficiently long.

4.2.1 Partitioning on firm age

Table 4 partitions observations based on firm age, measured as the number of years that the firm's earnings have been reported in *I/B/E/S*. Because samples in prior literature are comprised of mature firms, we separate observations into young firms versus mature firms to compare the relative forecast accuracy between the two groups. Panel A reveals that even one-year-ahead earnings are much more difficult to forecast for young firms than for mature firms. Specifically, for firms in their first year on *I/B/E/S*, the mean analysts' forecast error 11 months prior is 527 basis-points while the matching random walk forecast error is 534 basis-points. For firms that have been on *I/B/E/S* for at least five years, the mean analysts' forecast error is approximately half as large, at 268 basis-points, while the random walk forecast error is 301 basis-points. That is, it appears that mature firms are inherently more predictable, and although the random walk forecast error is much smaller for mature firms than for young firms, the superiority of analysts' forecasts is even greater. For firms in their first year on *I/B/E/S*, analysts' superiority is only 7 basis-points, but for the firms that are at least five years old, analysts' superiority is 33 basis-points, or almost five times better.

The second year forecast accuracy is even more striking. At month 23, firms that are less than four years old all exhibit negative values, indicating random walk forecast superiority. For firms in their first year on *I/B/E/S*, the differences are quite large, with random walk forecast superiority of 102 basis-points. Thus, for firms in their first year on *I/B/E/S*, analysts' forecasts are less accurate than random walk forecasts by more than one percent of price at the 23 month forecast horizon. In contrast, for firms that have been on *I/B/E/S* for at least five years, analysts' forecasts are more accurate than random walk forecasts by 8 basis points for the same forecast horizon.

Panel C of table 3 presents analysts' superiority results in FY3. These results mirror those of FY1 and FY2. For FY3, each group of firms reveals time-series forecast superiority at month 35, but this time-series forecast superiority declines as analysts gain information and timing advantages.

4.2.2 Partitioning on firm size

Table 5 partitions observations based on firm size. Specifically, each year, we partition all firms on *Compustat* with positive sales into two groups (large firms and small firms) using the median sales in the year as the threshold. Because *I/B/E/S* firms are generally larger than *Compustat* firms, fewer than half of the firms are classified as small using this threshold. As reported in panel A, analysts' superiority for small firms is much smaller than for large firms. For small firms, random walk is superior at 11 months prior to the earnings announcement in FY1, and in 6 and 11 of the 12 monthly forecasts for FY2 and FY3, respectively. Some of these differences are economically significant. For example, at the 23 month forecast horizon, the difference is almost one percent of price, and at the 35 month forecast horizon, the difference is almost one and a half percent of price.

4.2.3 Partitioning on analyst following

In panel B, we report similar results for lightly followed firms (i.e., those with one or two analysts). While analysts' forecasts are superior in most months, for early fiscal-year forecasts (e.g., 11 months prior), there is no difference in the accuracy of random walk forecasts and analysts' forecasts. Consistent with the results in table 4, results for FY2 and FY3 are similar, with random walk forecasts dominating analysts' forecasts at numerous forecast horizons.

4.3 The Relation between Analysts' Superiority and Absolute Forecasted Change in EPS

As discussed above, when analysts forecast no change in EPS, the random walk forecast and the analysts' forecasts are equal. Thus, to examine whether analysts' superiority varies with the forecasted change in EPS, we partition the observations into small, moderate, and large forecasted changes in EPS. For this analysis, we calculate the absolute value of the analysts' forecasted change in EPS and let the lowest and highest 33 percent represent small and large forecasted changes respectively. The difference in analysts' superiority between the extreme forecasts and the moderate forecasts is always large, but the direction of the effect differs for short and long forecast horizons.

4.3.1 FY1 forecasts

We find that for short horizons (i.e., first year forecasts), analysts' superiority is strongest when the forecasted absolute change in EPS is extreme. At the one month forecast horizon (i.e., one month prior to the earnings announcement), for the group of firms with the smallest forecasted change, analysts' superiority is only 26 basis points, but for the group of firms with the largest forecasted change, analysts' superiority is greater than 600 basis points. However, this relative superiority deteriorates as the horizon lengthens. For example, for the group of firms with small forecasted changes, analysts' superiority is only 12 basis points 10 months prior to the earnings announcement, while at the same horizon, analysts' superiority is 143 basis points for the group of firms with large forecasted changes. Although analysts' superiority diminishes as the horizon lengthens, in the first year, analysts' superiority is always significantly greater for the group of firms with large forecasted changes in EPS than for the group of firms with small forecasted changes in EPS.

4.3.2 FY2 forecasts

The results differ over longer horizons. For the group of firms with small forecasted changes, analysts' forecasts are more accurate than random walk forecasts over each of the 36 monthly horizons. However, for the group of firms with large forecasted changes, random walk dominates in a large number of forecast horizons. At 23 months prior to the earnings announcement, when analysts have no timing advantage and a slight information advantage, random walk forecasts are 40 basis points more accurate than analysts' forecasts for the group of firms with large forecasted changes and analysts' forecasts are 29 basis points more accurate than random walk forecasts for the group of firms with small forecasted changes. However, analysts are not superior to random walk for the group of firms with large forecasted changes in FY2 until month 18, when analysts have a 5 month timing advantage. This compares to month 21 for the full sample.

4.3.3 FY3 forecasts

The difference in accuracy between the groups with large versus small forecasted changes is even greater for forecasts made between 24 and 35 months prior to the earnings announcement. As with two-year-ahead forecasts, analysts' forecasts of three-year-ahead earnings are always superior to random walk forecasts for the group of firms with moderate forecasted changes in EPS. However, for the groups of firms with extreme forecasted changes, analysts' superiority is significantly positive in only 1 of the 12 forecast horizons; this occurs 24 months prior to the earnings announcement, when analysts have an 11 month timing advantage. From 27 to 35 months prior to the earnings announcement, random walk forecasts are superior to analysts' forecasts, and this difference is greater than 100 basis points at the 34 and 35 month horizons. In other words, when analysts forecast large changes in earnings three years in the future, a simple random walk estimate of those earnings is more accurate by one percent of price on average. Over the same horizon, when analysts forecast a small change in earnings, their forecasts are more accurate than a simple random walk by one half a percent of price.

4.4 Tests of Analysts' Superiority Using Market Expectations

Next, we examine the associations between time-series forecast errors and stock returns and between analysts' forecast errors and stock returns over various forecast horizons. To the extent that stock prices react to earnings surprises, higher associations between forecast errors and stock returns indicate a greater correspondence between the forecasts and ex ante market expectations. We regress stock returns measured from the month of the forecast through the month of the earnings announcement on forecast errors separately for random walk forecasts and analysts' forecasts using a seemingly unrelated regression system:

$$Return_{T,M} = \alpha + \beta\,(EPS_{T-1} - EPS_T) + \varepsilon_T \tag{4}$$

$$Return_{T,M} = \alpha + b\,(Forecasted\ EPS_{T,M} - EPS_T) + e_T \tag{5}$$

The coefficient β measures the relation between returns and random walk forecast errors, and the coefficient b measures the relation between returns and analysts' forecast errors. We report tests for the ratio of the regression coefficients β to b. We estimate this system for each of the 36 forecast horizons from 0 months prior (i.e., when analysts' forecasts and earnings are announced in the same month) to 35 months prior to the earnings announcement. Thus, we measure stock returns and forecast errors contemporaneously such that the returns accumulation period and the forecast horizon are equal. For example, when the forecast horizon is 12 months in length, the returns accumulation period is also 12 months in length and the forecast horizon and returns accumulation period represent the same 12 months.

In table 7, we present the estimation results for models (4) and (5) across all forecasting horizons. As the forecast horizon lengthens, the association between stock returns and forecast errors increases for both random walk and analysts' forecasts. The random walk coefficient ranges from 0.056 in the 1 month forecast horizon regression to 4.421 in the 24 month forecast horizon regression. Similarly, the analysts' forecast coefficient ranges from 0.163 in the 1 month forecast horizon regression to 4.286 in the 24 month forecast horizon regression. While the coefficients on both errors increase with the length of the forecast horizon, they grow at different rates.

We find that the relative weights that the market seems to assign to random walk forecast errors and analysts' forecast errors tend to track fairly closely to the accuracy tests in table 3. Over the shortest forecast horizon, when analysts' forecasts and earnings announcements coincide in the same calendar month, the association between stock returns and random walk forecast errors is just 34 percent of the association between stock returns and analysts' forecast errors. However, the relative magnitudes of the stock return associations grow nearly monotonically, so that at the 11 month forecast horizon, the random walk coefficient is 94 percent of the analysts' forecast error coefficient. To summarize, at the one year horizon, analysts' forecast errors dominate random walk-based forecast errors as a proxy for market expectations, which mirrors the accuracy results from table 3. However, the relative ability of analysts' forecasts to proxy for market expectations is much stronger at the one month forecast horizon than over longer forecast horizons.

The pattern for FY2 forecasts is similar, but analysts' forecasts are a significantly better proxy than random walk forecasts only for horizons shorter than 21 months. For the 23 month forecast horizon, the random walk forecast is a significantly better proxy for market expectations, on average. Finally, for forecasts of FY3, analysts' forecasts are a better proxy in only 7 of the 12 months. For forecast horizons of 33 through 35 months, random walk is again a significantly better proxy for market expectations. Overall, it appears that market expectations track fairly closely to the forecast accuracy results. Over horizons where analysts' forecasts are more accurate than random walk forecasts, analysts' forecasts seem to provide a better proxy for market expectations. However, over horizons where random walk forecasts are more accurate than analysts' forecasts, random walk forecasts seem to provide a better proxy for market expectations.

4.4.1 Partitioning on firm size and on analyst following

Table 8, Panels A and B present the estimation results for models (4) and (5) for small firms and for lightly followed firms, respectively. In Panel A, for FY1, we find that β/b ranges from 18 percent for the shortest forecast horizon to 94 percent for the 11 month forecast horizon. Moreover, analysts' forecasts are no better than random walk forecasts as a proxy for market expectations 10 and 11 months prior to the earnings announcement. For FY2 and FY3, we find that analysts' forecasts are no better than random walk forecasts over horizons of 20 through 23 months and 28 through 32 months prior to the earnings announcement, respectively, and that random walk forecasts dominate analysts' forecasts over horizons of 33 through 35 months prior.

The results for lightly followed firms are reported in Panel B, and are very similar to those reported in Panel A (for small firms) for FY1 and FY2. That is, analysts' forecasts dominate random walk forecasts as a proxy for market expectations only over shorter forecast horizons. However, the results for FY3 are striking. For three-year-ahead forecasts, analysts' forecasts are not a better proxy than random walk forecasts across all forecast horizons (i.e., from 24 through 35 months prior), and consistent with the results for small firms, random walk forecasts dominate over forecast horizons of 33 through 35 months. Overall, the results reported in table 8 for small and lightly followed firms are consistent with the analysts' forecast accuracy results reported in table 5.

4.4.2 Partitioning on the absolute forecasted change in EPS

Table 9, Panels A and B present the estimation results for models (4) and (5) for firms with small and large analysts' forecasts of the change in EPS, respectively. In Panel A, for FY1, we find no evidence of statistical differences between the coefficients on the random walk and analysts' forecast errors when analysts forecast the least extreme changes in EPS. Thus, analysts' forecasts are no better than random walk forecasts as a proxy for market expectations in the 11 months prior to the earnings announcement. For FY2 and FY3, we find that analysts' forecasts are no better than random walk forecasts as a proxy for market expectations over horizons of 21 through 23 months and 31 through 35 months prior to the earnings announcement, respectively.

In Table 9, Panel B, we present the results when analysts forecast the most extreme changes in EPS. For FY1, we find that analysts' forecasts dominate random walk forecasts as a proxy for market expectations in all months. However, in FY2, we find that random walk forecasts dominate analysts' forecasts over horizons greater than 19 months and, in FY3, we find that random walk forecasts dominate for horizons greater than 30 months. Overall, the market expectation results in Table 9 track fairly closely to the forecast accuracy results presented previously.

4.5 Multivariate Tests

As a final test, we investigate analysts' superiority in a multivariate setting which controls for the information environment of the firm and risk factors. Specifically, we estimate the following regression separately for each of the 36 forecast horizons:

$$Analysts'\,Superiority_{T,M} = \gamma_0 + \gamma_1\,\#Analysts_T + \gamma_2\,STD_{T,M} + \gamma_3\,BTM_{T-1}$$

$$+\gamma_4\,Sales_{\,T-1} + \gamma_5\,Forecast\Delta_{T,M} + \varepsilon_T \qquad (6)$$

where *#Analysts* is the number of analysts in the consensus forecast of EPS in year T made in month M; *STD* is the standard deviation of analysts' forecasts for year T earnings as measured in month M; *BTM* is the book-to-market ratio (from *Compustat*) measured at the end of year T-1; *Sales* (from *Compustat*) is measured at the end of year T-1; and *ForecastΔ* is the absolute value of the forecasted change in EPS (i.e., *Forecasted EPS* – EPS_{T-1}) implied by the analysts' forecast of year T earnings as measured in month M.

In table 10, we present the estimation results for equation (6) for each of the 36 forecast horizons. We find that the number of analysts' estimates, standard deviation of the estimates, book-to-market ratio, sales revenue (size), and the analysts' forecasted change in earnings are all significantly related to the level of analysts' superiority over almost every horizon. Although several of the factors (such as the number of analysts and sales) are correlated with one another, each is significantly related to analysts' superiority over the vast majority of horizons. The most consistent and strongest relation is with the forecasted change in earnings, which is highly significant at every horizon. For forecasts that are in the same fiscal year as the earnings being forecasted (i.e., FY1 forecasts), the coefficient on the absolute forecasted change is consistently positive, revealing that more extreme analysts' forecasts are more accurate than random walk forecasts when the forecast horizon is less than 12 months. However, over every forecast horizon greater than 12 months prior to the earnings announcement, the opposite is true – the more extreme the forecast (so the farther from the prior year's reported earnings), the less accurate are analysts relative to random walk. This is true even after controlling for the number of forecasts, variance in those forecasts, size, and book-to-market.

5. Conclusion

In this paper, we show that the widely held belief that analysts' forecasts are superior to time-series forecasts is not fully descriptive. Although analysts' earnings forecasts consistently beat random walk earnings forecasts over short windows, for longer forecasting horizons, analysts' superiority declines, and at certain horizons, analysts' forecasts are dominated by random walk forecasts. This is especially true for small firms, young firms, thinly followed firms, and when analysts forecast more extreme changes in earnings. We link this finding to stock returns, and show that the market seems to rely on random walk forecasts (or similar simple models of earnings) at longer horizons, but tends towards analysts' forecasts as the forecast horizon becomes shorter.

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' forecasts lose their relative superiority to time-series forecasts. In fact, we show that even a simple random walk forecast performs as well, in both an economic and statistical sense, relative to analysts' forecasts. This is important because analysts' forecasts are not available for a large number of firms. Our findings suggest investors can reasonably rely on random walk forecasts when implementing long-term buy-and-hold valuation strategies, 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. In addition, because our results suggest that the use of a simple random walk model to form forecasts in securities analysis is feasible, we suggest that declining analyst coverage alleged to have resulted from increased regulation in the securities industry (Mohanram and Sunder 2006) may be less detrimental than some assume.

It is important to note that our results do not refute the results of studies that use analysts' forecasts to proxy for market expectations. Moreover, our finding that random walk forecasts are more accurate than analysts' forecasts over long horizons does not imply that random walk forecasts would improve prediction models of firm value, the cost of capital, or stock returns. We leave these issues for future research.

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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	One to five 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	One to four quarters ahead.	Four quarters out, analysts' forecast errors are 31.7% compared to the best TS error of 32.9%. One quarter out, mean analysts' forecast error are 9.7% compared to 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.	Random walk and 7 other TS models, requiring at least 12 years (48 quarters) of data.		One to four quarters ahead.	Four quarters out (annual), absolute analysts' forecasts errors are 22.5% compared to absolute forecast errors of 26.1% for random walk.	Number of days separating TS and analysts' forecast – positive
Brown, Hagerman, Griffin, and Zmijewski (1987)	233 firms from the 1975 through 1980.	3 TS models, requiring a minimum of 60 quarters of data.	Winsorized forecast errors at 1.0	One, two, and three quarters ahead.	Three-quarters-ahead, analysts' forecast errors are 28.7% and TS forecast errors are 33%.	Forecast horizon – negative
Brown, Richardson, and Schwager (1987)	Sample 1: 168 firms from Q1-1977 through Q4-1979.	Quarterly random-walk model.		One, two, and three quarters ahead.	For the one 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, Richardson, and Schwager (1987)	Sample 2: 168 firms from 1977 through 1979.	Annual random-walk model.		Horizons of 1, 6, and 18 months prior to the fiscal year-end date.	For the one 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, Richardson, and Schwager (1987)	Sample 3: 702 firms from 1977 through 1982.	Annual random-walk 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 one 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 (one year), analysts' forecast errors are $0.74 compared to TS forecast errors of $0.96.	Forecast horizon – positive
Kross, Ro, and Schroeder (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
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, Lorek, and Pagach (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

Table 2: Descriptive statistics

Panel A: Firm Characteristics

	Mean	Median	Q1	Q3
Sales	374	374	110	1,384
BTM	0.5813	0.5029	0.3146	0.7456
Age	8.217	7	4	12
# Analysts	7.62	5	2	10

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.

Panel B: % of Forecast Errors Greater than Absolute Value of Reported Earnings

Months Prior to Earnings Announcement Date	**Analysts' Forecasts Errors**	**Random Walk Errors**
Mature firms:		
1 Month	2.9%	10.5%
All firms:		
1 Month	5.2%	14.2%
11 Months	16.5%	14.6%
23 Months	22.6%	19.7%
35 Months	29.5%	26.2%

Panel percentages represent the proportion of forecast errors that exceed 100% of realized earnings. In the first row, the sample is restricted to mature firms with at least 10 prior years of annual EPS reported on *I/B/E/S*.

Panel C: Signed Forecast Errors

	Mean	**Median**	**Q1**	**Q3**
Signed Random Walk Errors				
11 Months	0.0086	-0.0055	-0.0153	0.0108
23 Months	0.0033	-0.0091	-0.0260	0.0150
35 Months	-0.0038	-0.0124	-0.0363	0.0166
Signed Analysts' Forecasts Errors				
11 Months	0.0194	0.0028	-0.0041	0.0209
23 Months	0.0272	0.0090	-0.0049	0.0391
35 Months	0.0332	0.0162	-0.0047	0.0541

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.

Table 3: Main Results
Analysts' Forecast Superiority, Full Sample

FY1			FY2			FY3		
Months Prior	**Firm-years**	**Analyst Superiority**	**Months Prior**	**Firm-years**	**Analyst Superiority**	**Months Prior**	**Firm-years**	**Analyst Superiority**
0	32,723	0.0245	12	29,072	0.0120	24	21,944	0.0072
1	66,224	0.0236	13	55,447	0.0106	25	41,766	0.0055
2	66,104	0.0227	14	56,659	0.0095	26	42,827	0.0044
3	65,794	0.0212	15	56,575	0.0081	27	42,941	0.0033
4	65,458	0.0182	16	56,023	0.0063	28	42,588	0.0019
5	65,158	0.0155	17	55,360	0.0049	29	42,272	0.0007
6	64,787	0.0131	18	54,458	0.0037	30	41,753	(0.0000) NS
7	64,361	0.0102	19	53,195	0.0022	31	40,952	(0.0012)
8	63,869	0.0081	20	51,832	0.0012	32	40,137	(0.0020)
9	63,200	0.0064	21	49,745	0.0004	33	38,925	(0.0027)
10	62,103	0.0041	22	46,501	(0.0006)	34	36,836	(0.0035)
11	60,289	0.0025	23	42,124	(0.0011)	35	33,789	(0.0040)

The table reports the mean difference between absolute random walk errors and absolute analysts' forecast errors 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. NS Indicates not significant at the 5 percent level, two-tailed. All other values are significant (almost all at $p < 0.0001$).

Table 4: Analysts' Forecast Superiority and Firm Age

Panel A: FY1 – 11 months prior to RDQE

Firm Age	Firm-years	Analysts' Superiority	RW Forecast Error	Analysts' Forecast Error
1	2,534	0.0007	0.0534	0.0527
2	6,321	0.0015	0.0405	0.0391
3	5,867	0.0005	0.0382	0.0378
4	5,109	0.0005	0.0379	0.0374
5+	40,335	0.0033	0.0301	0.0268

Panel B: FY2 – 23 months prior to RDQE

Firm Age	Firm Years	Analysts' Superiority	RW Forecast Error	Analysts' Forecast Error
1	1,413	(0.0102)	0.0628	0.0730
2	3,969	(0.0072)	0.0528	0.0599
3	3,810	(0.0048)	0.0511	0.0559
4	3,404	(0.0028)	0.0472	0.0500
5+	29,447	0.0008	0.0396	0.0388

Panel C: FY3 – 35 months prior to RDQE

Firm Age	Firm Years	Analysts' Superiority	RW Forecast Error	Analysts' Forecast Error
1	1,119	(0.0186)	0.0735	0.0871
2	2,954	(0.0147)	0.0647	0.0785
3	3,011	(0.0084)	0.0604	0.0670
4	2,794	(0.0060)	0.0584	0.0618
5+	23,868	(0.0012)	0.0498	0.0488

The table reports the mean difference between absolute random walk errors and absolute analysts' forecast errors 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. [NS] Indicates not significant at the 5 percent level, two-tailed. All other values are significant (almost all at $p < 0.0001$).

Table 5: Analysts' Forecast Superiority for Small Firms

Panel A: Small Firms

FY1			FY2				FY3		
Months Prior	**Firm-years**	**Analysts' Superiority**	**Months Prior**	**Firm-years**	**Analysts' Superiority**		**Months Prior**	**Firm-years**	**Analysts' Superiority**
0	6,897	0.0256	12	5,786	0.0085		24	3,067	0.0007
1	13,845	0.0252	13	10,871	0.0074		25	6,006	(0.0023)
2	13,737	0.0242	14	11,087	0.0060		26	6,192	(0.0040)
3	13,535	0.0225	15	10,885	0.0045		27	6,114	(0.0054)
4	13,396	0.0191	16	10,574	0.0020		28	5,968	(0.0074)
5	13,175	0.0162	17	10,204	0.0004	NS	29	5,836	(0.0086)
6	13,009	0.0132	18	9,799	(0.0012)		30	5,626	(0.0096)
7	12,815	0.0098	19	9,299	(0.0026)		31	5,366	(0.0106)
8	12,607	0.0071	20	8,759	(0.0040)		32	5,055	(0.0119)
9	12,341	0.0052	21	8,023	(0.0055)		33	4,707	(0.0131)
10	11,906	0.0023	22	6,987	(0.0066)		34	4,152	(0.0151)
11	11,314	(0.0003)	23	5,804	(0.0078)		35	3,521	(0.0167)

Panel B: Low Analyst Following

FY1			FY2				FY3			
Months Prior	**Firm-years**	**Analysts' Superiority**	**Months Prior**	**Firm-years**	**Analysts' Superiority**		**Months Prior**	**Firm-years**	**Analysts' Superiority**	
0	9,089	0.0314	12	8,001	0.0110		24	8,634	0.0063	
1	18,744	0.0311	13	14,945	0.0102		25	16,197	0.0036	
2	18,704	0.0289	14	15,648	0.0085		26	16,784	0.0022	
3	18,557	0.0267	15	15,890	0.0066		27	16,848	0.0005	NS
4	18,422	0.0224	16	16,055	0.0043		28	16,672	(0.0014)	
5	18,265	0.0185	17	16,138	0.0027		29	16,489	(0.0030)	
6	18,104	0.0151	18	16,319	0.0008	NS	30	16,180	(0.0035)	
7	18,062	0.0109	19	16,646	(0.0009)		31	15,556	(0.0051)	
8	17,880	0.0080	20	16,901	(0.0022)		32	14,941	(0.0063)	

9	17,636	0.0058	21	17,310	(0.0032)	33	13,992	(0.0074)
10	17,113	0.0026	22	17,924	(0.0041)	34	12,501	(0.0087)
11	16,264	0.0000 [NS]	23	18,185	(0.0045)	35	10,544	(0.0099)

The table reports the mean difference between absolute random walk errors and absolute analysts' forecast errors 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. [NS] Indicates not significant at the 5 percent level, two-tailed. All other values are significant (almost all at $p < 0.0001$).

Table 6: Analysts' Forecast Superiority
Observations Partitioned by the Magnitude of the Forecasted Change in EPS

Panel A: The 33% of Forecasts with the Least Extreme Forecasted Change in EPS

FY1			FY2			FY3		
Months Prior	**Firm-years**	**Analysts' Superiority**	**Months Prior**	**Firm-years**	**Analysts' Superiority**	**Months Prior**	**Firm-years**	**Analysts' Superiority**
0	10,915	0.0025	12	9,679	0.0174	24	7,305	0.0140
1	22,093	0.0026	13	18,472	0.0156	25	13,910	0.0124
2	22,053	0.0025	14	18,881	0.0143	26	14,268	0.0115
3	21,954	0.0023	15	18,845	0.0125	27	14,300	0.0106
4	21,842	0.0020	16	18,654	0.0106	28	14,185	0.0097
5	21,743	0.0018	17	18,439	0.0087	29	14,075	0.0085
6	21,620	0.0016	18	18,139	0.0074	30	13,907	0.0078
7	21,481	0.0014	19	17,721	0.0058	31	13,645	0.0071
8	21,324	0.0013	20	17,260	0.0051	32	13,382	0.0065
9	21,110	0.0012	21	16,561	0.0041	33	12,968	0.0061
10	20,731	0.0012	22	15,488	0.0034	34	12,277	0.0057
11	20,117	0.0012	23	14,023	0.0029	35	11,263	0.0053

Panel B: The 33% of Forecasts with the Most Extreme Forecasted Change in EPS

FY1			FY2			FY3			
Months Prior	**Firm-years**	**Analysts' Superiority**	**Months Prior**	**Firm-years**	**Analysts' Superiority**	**Months Prior**	**Firm-years**	**Analysts' Superiority**	
0	20,131	0.0025	12	9,695	0.0090	24	7,319	0.0018	
1	10,881	0.0616	13	18,483	0.0077	25	13,924	0.0005	NS
2	22,029	0.0591	14	18,885	0.0067	26	14,272	(0.0007)	NS
3	21,988	0.0566	15	18,865	0.0057	27	14,316	(0.0021)	
4	21,881	0.0530	16	18,684	0.0042	28	14,196	(0.0037)	
5	21,761	0.0453	17	18,463	0.0028	29	14,088	(0.0049)	
6	21,657	0.0381	18	18,157	0.0014	30	13,908	(0.0058)	

7	21,530	0.0320	19	17,728	0.0000 [NS]	31	13,639	(0.0076)
8	21,385	0.0244	20	17,276	(0.0012)	32	13,360	(0.0087)
9	21,217	0.0190	21	16,584	(0.0025)	33	12,964	(0.0095)
10	20,993	0.0143	22	15,498	(0.0035)	34	12,267	(0.0109)
11	20,635	0.0083	23	14,042	(0.0040)	35	11,256	(0.0115)

Observations are partitioned into thirds based on the analysts' forecasted change in EPS as a percentage of price. The table reports the mean difference between absolute random walk errors and absolute analysts' forecast errors 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. [NS] Indicates not significant at the 5 percent level, two-tailed. All other values are significant (almost all at $p < 0.0001$).

Table 7: Market Expectations
Random Walk Forecast Error versus Analysts' Forecast Error and Market Returns

$$Return_{T,M} = \alpha + \beta\,(EPS_{T-1} - EPS_T) + \varepsilon_T$$

$$Return_{T,M} = \alpha + b\,(Forecasted\ EPS_{T,M} - EPS_T) + e_T$$

FY1			FY2			FY3		
Months Prior	Firm-years	β/b	Months Prior	Firm-years	β/b	Months Prior	Firm-years	β/b
0	30,411	0.345	12	28,003	0.602	24	21,097	0.784
1	62,355	0.395	13	53,654	0.678	25	40,377	0.831
2	63,455	0.342	14	54,664	0.707	26	41,336	0.843
3	63,419	0.396	15	54,473	0.742	27	41,369	0.874
4	63,101	0.540	16	53,882	0.798	28	40,992	0.908
5	62,790	0.632	17	53,196	0.833	29	40,674	0.928
6	62,441	0.685	18	52,319	0.888	30	40,151	0.962
7	62,016	0.735	19	51,113	0.912	31	39,409	1.001
8	61,540	0.795	20	49,789	0.953	32	38,624	1.017 NS
9	60,915	0.838	21	47,783	1.007 NS	33	37,455	1.057 NS
10	59,936	0.905	22	44,672	1.008 NS	34	35,435	1.081
11	58,261	0.939	23	40,500	1.032	35	32,530	1.099

In this table, we regress returns on random walk forecast errors and analysts' forecast errors separately. Returns are compounded raw monthly returns from CRSP, calculated beginning in the month that the forecast is issued and ending as of the end of the month of the earnings announcement. The first column is the number of months prior to the earnings announcements date that the analysts' forecast is made. The second column is the number of firm-years with sufficient data to calculate forecast errors for both random walk and analysts, and with stock market returns over the horizon. The third column is the ratio of the coefficient on the random walk error to the coefficient on the analysts' forecast error. [NS] indicates that the difference between the estimates of the β and b coefficients is not significantly different at the 5 percent level, two-sided. All other differences are statistically significant.

Table 8: Market Expectations Subsamples

Random Walk Forecast Error versus Analysts' Forecast Error and Market Returns

$$Return_{T,M} = \alpha + \beta\,(EPS_{T-1} - EPS_T) + \varepsilon_T$$

$$Return_{T,M} = \alpha + b\,(Forecasted\ EPS_{T,M} - EPS_T) + e_T$$

Panel A: Small Firms

FY1				FY2				FY3			
Months Prior	Firm-years	*β/b*		Months Prior	Firm-years	*β/b*		Months Prior	Firm-years	*β/b*	
0	6,558	0.1813		12	7,275	0.6957		24	3,396	0.9083	
1	13,382	0.3422		13	13,711	0.7238		25	6,575	0.8822	
2	13,474	0.4286		14	14,068	0.7550		26	6,814	0.9084	
3	13,364	0.4433		15	13,887	0.7793		27	6,757	0.9330	
4	13,227	0.5309		16	13,468	0.8111		28	6,552	0.9392	NS
5	13,001	0.6186		17	12,974	0.8496		29	6,422	0.9495	NS
6	12,838	0.6610		18	12,424	0.9076		30	6,173	0.9550	NS
7	12,643	0.7170		19	11,713	0.8973		31	5,844	0.9762	NS
8	12,431	0.8323		20	10,906	0.9676	NS	32	5,491	1.0016	NS
9	12,176	0.8551		21	9,808	1.0151	NS	33	5,028	1.0965	
10	11,750	0.9273	NS	22	8,168	1.0043	NS	34	4,258	1.1229	
11	11,167	0.9431	NS	23	6,392	1.0277	NS	35	3,431	1.1230	

Panel B: Low analyst following

FY1				FY2				FY3			
Months Prior	Firm-years	*β/b*		Months Prior	Firm-years	*β/b*		Months Prior	Firm-years	*β/b*	
0	8,522	0.4728		12	5,691	0.6681		24	3,010	0.9507	NS
1	17,567	0.5084		13	10,710	0.6871		25	5,901	0.9674	NS
2	17,746	0.4986		14	10,912	0.7337		26	6,077	0.9682	NS
3	17,688	0.5739		15	10,706	0.7421		27	5,993	0.9786	NS
4	17,582	0.6328		16	10,395	0.8069		28	5,842	1.0100	NS
5	17,437	0.7040		17	10,026	0.8506		29	5,706	1.0230	NS
6	17,289	0.7165		18	9,631	0.9414	NS	30	5,502	1.0464	NS
7	17,220	0.7617		19	9,140	0.9273	NS	31	5,247	1.0736	NS
8	17,039	0.8377		20	8,606	0.9721	NS	32	4,941	1.0892	NS
9	16,825	0.9025		21	7,878	1.0209	NS	33	4,596	1.1288	
10	16,383	0.9530	NS	22	6,849	1.0100	NS	34	4,045	1.2025	
11	15,615	0.9823	NS	23	5,687	1.0570	NS	35	3,426	1.1849	

In this table, we regress returns on random walk forecast errors and analysts' forecast errors separately. Returns are compounded raw monthly returns from CRSP, calculated beginning in the month that the forecast is issued and ending as of the end of the month of the earnings announcement. The first column is the number of months prior to the earnings announcements date that the analysts' forecast is made. The second column is the number of firm-years with sufficient data to calculate forecast errors for both random walk and analysts, and with stock market returns over the horizon. The third column is the ratio of the coefficient on the random walk error to the coefficient on the analysts' forecast error. [NS] indicates that the difference between the estimates of the β and b coefficients is not significantly different at the 5 percent level, two-sided. All other differences are statistically significant.

Table 9: Market Expectations Subsamples
Observations Partitioned by the Magnitude of the Forecasted Change in EPS

$$Return_{T,M} = \alpha + \beta\,(EPS_{T-1} - EPS_T) + \varepsilon_T$$

$$Return_{T,M} = \alpha + b\,(Forecasted\ EPS_{T,M} - EPS_T) + e_T$$

Panel A: The 33% of Forecasts with the Least Extreme Forecasted Change in EPS

FY1				FY2				FY3			
Months Prior	Firm-Years	β/b		Months Prior	Firm-years	β/b		Months Prior	Firm-years	β/b	
0	9,023	0.9388	NS	12	7,763	0.6330		24	5,840	0.7597	
1	18,254	0.9280	NS	13	14,935	0.7053		25	11,227	0.7974	
2	18,188	0.9300	NS	14	15,145	0.7316		26	11,462	0.8336	
3	18,083	0.9620	NS	15	15,057	0.7808		27	11,466	0.8514	
4	18,018	0.9882	NS	16	14,865	0.8222		28	11,356	0.8433	
5	17,921	0.9764	NS	17	14,697	0.8603		29	11,264	0.8631	
6	17,807	0.9807	NS	18	14,479	0.8661		30	11,101	0.9067	
7	17,710	0.9866	NS	19	14,147	0.9241		31	10,891	0.9716	NS
8	17,566	0.9767	NS	20	13,783	0.9412		32	10,696	0.9870	NS
9	17,398	0.9794	NS	21	13,218	0.9643	NS	33	10,337	1.0165	NS
10	17,143	0.9772	NS	22	12,365	0.9747	NS	34	9,777	1.0334	NS
11	16,646	0.9791	NS	23	11,269	0.9930	NS	35	9,034	1.0473	NS

Panel B: The 33% of Forecasts with the Most Extreme Forecasted Change in EPS

FY1			FY2			FY3			
Months Prior	Firm-Years	β/b	Months Prior	Firm-years	β/b	Months Prior	Firm-years	β/b	
0	8,795	0.2981	12	7,575	0.5937	24	5,566	0.8875	
1	17,647	0.3710	13	14,701	0.6814	25	10,831	0.8781	
2	17,619	0.3270	14	14,892	0.7739	26	10,975	0.8875	
3	17,498	0.3560	15	14,823	0.7831	27	10,950	0.9032	
4	17,319	0.5213	16	14,617	0.7384	28	10,811	0.9513	NS
5	17,210	0.6093	17	14,426	0.8124	29	10,741	0.9741	NS
6	17,103	0.6808	18	14,171	0.9003	30	10,587	0.9953	NS
7	16,903	0.7110	19	13,800	0.9175	31	10,376	1.0477	
8	16,709	0.7550	20	13,433	1.0186	32	10,130	1.0967	
9	16,438	0.7822	21	12,856	1.0476	33	9,823	1.0626	
10	16,084	0.8471	22	11,983	1.0304	34	9,269	1.1096	
11	15,650	0.8717	23	10,852	1.0735	35	8,493	1.1257	

In this table, we regress returns on random walk forecast errors and analysts' forecast errors separately. Returns are compounded raw monthly returns from CRSP, calculated beginning in the month that the forecast is issued and ending as of the end of the month of the earnings announcement. The first column is the number of months prior to the earnings announcements date that the analysts' forecast is made. The second column is the number of firm-years with sufficient data to calculate forecast errors for both random walk and analysts, and with stock market returns over the horizon. The third column is the ratio of the coefficient on the random walk error to the coefficient on the analysts' forecast error. [NS] indicates that the difference between the estimates of the β and b coefficients is not significantly different at the 5 percent level, two-sided. All other differences are statistically significant.

Table 10: Multivariate Regression of Analysts' Superiority by Months Prior to Earnings Announcement Date

$$Analysts'\ Superiority_{T,M} = \gamma_0 + \gamma_1\ \#Analysts_T + \gamma_2\ STD_{T,M} + \gamma_3\ BTM_{T-1} + \gamma_4\ Sales_{\ T-1} + \gamma_5\ Forecast\Delta_{T,M} + \varepsilon_T$$

Months Prior RDQE	Intercept	#Analysts	STD	BTM	Sales	Forecasted Δ
0	-0.0083	-0.0021	0.0055	0.0035	0.0015^{NS}	0.0279
1	-0.0072	-0.0022	0.0052	0.0028	0.0017	0.0262
2	-0.0079	-0.0013	0.0043	0.0030	0.0017	0.0253
3	-0.0079	-0.0013	0.0047	0.0029	0.0012	0.0238
4	-0.0071	-0.0005	0.0039	0.0024	0.0005^{NS}	0.0206
5	-0.0055	0.0003^{NS}	0.0027	0.0025	-0.0002^{NS}	0.0175
6	-0.0054	0.0006	0.0025	0.0022	0.0001^{NS}	0.0148
7	-0.0050	0.0011	0.0015	0.0019	0.0004^{NS}	0.0115
8	-0.0047	0.0015	0.0009	0.0017	0.0007^{NS}	0.0092
9	-0.0041	0.0016	0.0004	0.0015	0.0010	0.0069
10	-0.0026	0.0015	-0.0003	0.0010	0.0012	0.0043
11	-0.0017	0.0018	-0.0011	0.0008	0.0012	0.0025
12	0.0076	-0.0002^{NS}	0.0050	0.0045	0.0058	-0.0064
13	0.0070	0.0003^{NS}	0.0031	0.0041	0.0055	-0.0057
14	0.0056	0.0008	0.0031	0.0042	0.0053	-0.0057
15	0.0046	0.0011	0.0020	0.0042	0.0049	-0.0050
16	0.0028	0.0017	0.0010	0.0037	0.0052	-0.0048
17	0.0012	0.0022	0.0000^{NS}	0.0036	0.0054	-0.0043
18	0.0005^{NS}	0.0028	-0.0007	0.0036	0.0048	-0.0043
19	-0.0015	0.0031	-0.0014	0.0033	0.0049	-0.0037
20	-0.0023	0.0037	-0.0019	0.0030	0.0048	-0.0035
21	-0.0029	0.0038	-0.0023	0.0026	0.0054	-0.0036
22	-0.0036	0.0038	-0.0028	0.0024	0.0057	-0.0035
23	-0.0079	0.0057	-0.0027	0.0019	0.0062	-0.0035
24	0.0048	0.0009	-0.0005^{NS}	0.0051	0.0094	-0.0074
25	0.0026	0.0023	-0.0016	0.0059	0.0090	-0.0074
26	0.0026	0.0025	-0.0023	0.0056	0.0093	-0.0078
27	0.0019	0.0029	-0.0026	0.0053	0.0094	-0.0083
28	0.0007^{NS}	0.0035	-0.0028	0.0052	0.0096	-0.0089
29	-0.0007^{NS}	0.0039	-0.0028	0.0047	0.0096	-0.0090
30	-0.0020	0.0042	-0.0033	0.0046	0.0106	-0.0093
31	-0.0027	0.0046	-0.0035	0.0042	0.0104	-0.0097
32	-0.0036	0.0049	-0.0038	0.0038	0.0108	-0.0099

33	-0.0040	0.0051	-0.0040	0.0035	0.0111	-0.0103
34	-0.0060	0.0054	-0.0044	0.0030	0.0133	-0.0108
35	-0.0062	0.0058	-0.0048	0.0019	0.0127	-0.0108

In this table, we regress analysts' superiority on a number of factors separately for each of the 36 forecast horizons. # Analysts is the number of analysts following measured as NUMEST for the statistical period 11 months prior to the report date of annual earnings. *STD* is the standard deviation of analysts' forecasts for year T earnings as measured in month M. Book-to-Market (BTM) and Sales are measured as of the end of the base year. *Forecast*Δ is the absolute value of forecasted change in EPS (i.e., *Forecasted EPS – EPS_{T-1}*) implied by the analysts' forecast of year T earnings as measured in month M. ^{NS} indicates that the coefficient is not significantly different from zero at the 5 percent level, two-sided.

Figure 1: Number of Firms with Available Data in Compustat and CRSP that are Uncovered in I/B/E/S

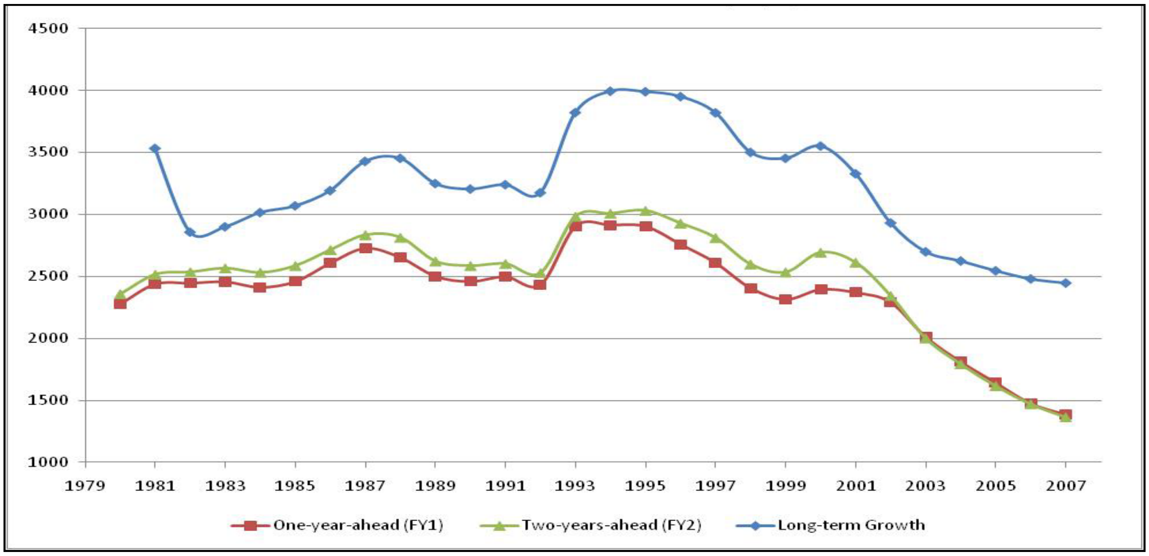

Figure 2: Percentage of Firms with Available Data in Compustat and CRSP that are Uncovered in I/B/E/S

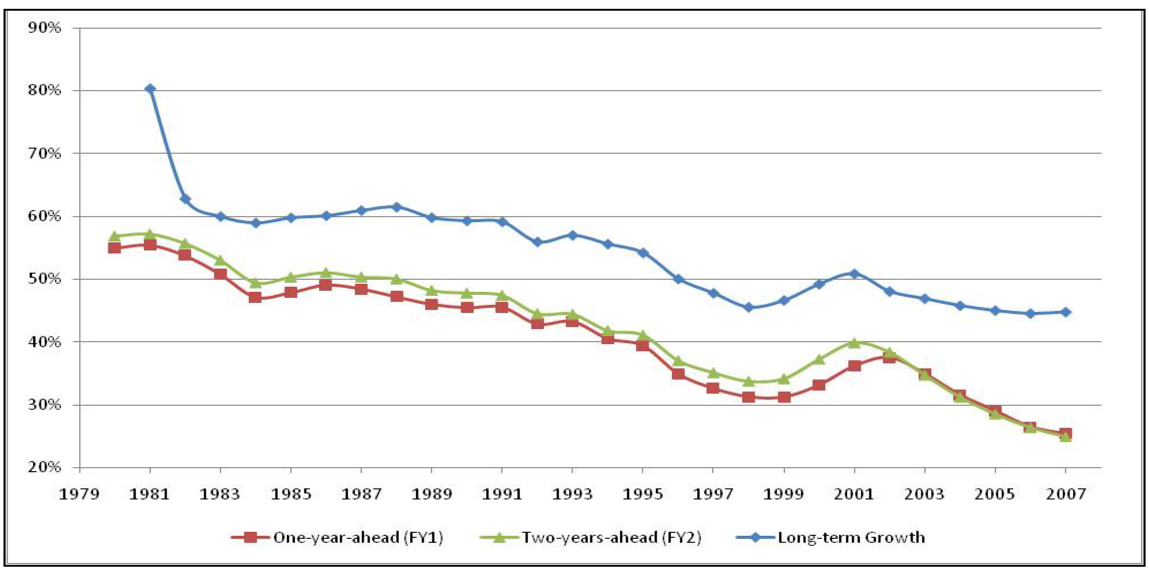

Figure 3: Mean Assets for Firms with and without One-year-ahead Earnings Forecasts in I/B/E/S

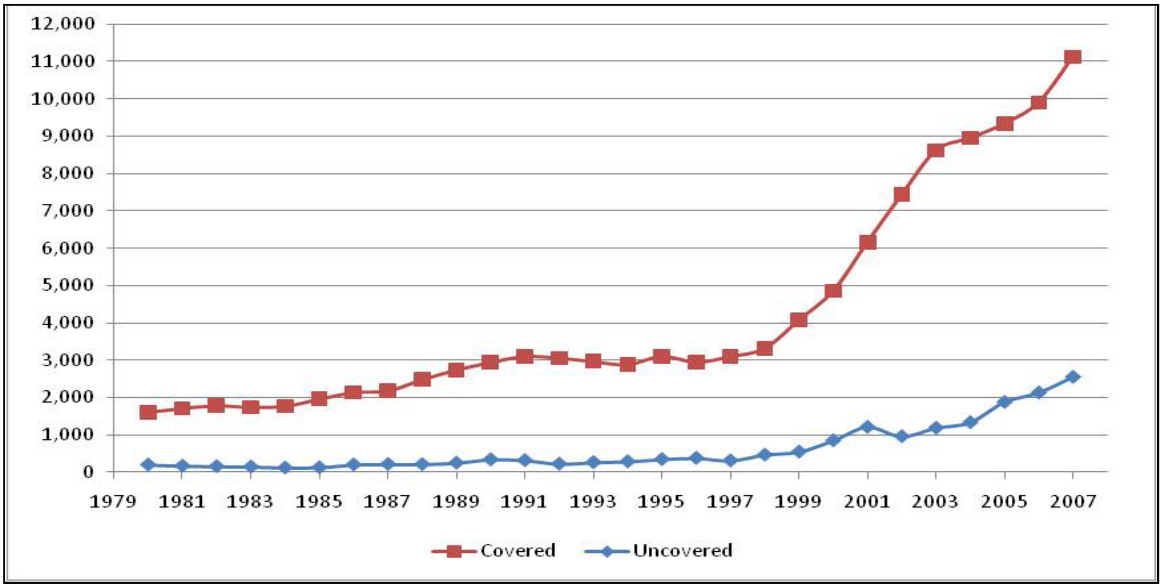

Figure 4: Median Assets for Firms with and without One-year-ahead Earnings Forecasts in I/B/E/S