A New Approach to Predicting Analyst Forecast Errors: Do Investors Overweight Analyst Forecasts?

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Abstract

I provide evidence that investors systematically overweight analyst forecasts by demonstrating that prices do not fully reflect the predictable component of analyst forecast errors. This evidence conflicts with conclusions in prior research relying on traditional approaches to predicting analyst errors. I highlight estimation bias associated with traditional approaches and develop a new approach that reduces this bias by directly forecasting future earnings. I estimate 'characteristic forecasts' using large sample relations to map current firm characteristics into forecasts of future earnings. Contrasting characteristic and analyst forecasts predicts future analyst forecast errors, forecast revisions, and changes in buy/sell recommendations. I document abnormal returns to a strategy that sorts firms based on predicted forecast errors, consistent with investors overweighting analyst forecasts relative to optimal Bayesian weights. Overweighting varies intuitively with characteristics of the information environment and across investor sentiment regimes. Taken together, the evidence suggests that predictable biases in analyst forecasts influence the information content of prices.

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1. Introduction

Estimating a firm's future profitability is an essential part of valuation analysis. Analysts can facilitate the valuation process by translating a mixture of public and private information into forecasts of future earnings. However, a substantial literature spanning finance, economics, and accounting raises concerns about the use of these forecasts for investment decisions, commonly citing a significant incentive misalignment between analysts and those of the end users of the earnings forecasts.[1] The collective evidence from this literature suggests that reliance on analyst forecasts can produce biased estimates of firm value.

Recognition of this problem has motivated researchers to develop techniques to identify the predictable component of analyst forecast errors. The development of these techniques also reflects a desire to better understand what information is reflected in price. To the extent that investors overweight analyst forecasts, a firm's share price is unlikely to fully reflect the earnings news associated with predictable analyst forecast errors.[2] Thus, if overweighting is systematic, the identification of predictable forecast errors is potentially useful in disciplining prices. The goal of this paper is to determine whether and to what extent investors systematically overweight analysts' earnings forecasts.

Motivated by a similar goal, Hughes, Liu, and Su (2008) concludes that investors do *not* overweight analyst forecasts. They find that a strategy of sorting firms by predicted forecast errors fails to generate abnormal returns and attribute this finding to market efficiency with respect to the predictable component of analyst errors. I argue that their findings are unlikely to result from market efficiency and are instead an artifact of their methodology.

The traditional approach to predicting forecast errors, used by Hughes, Liu, and Su (2008) among others, involves regressing realized forecast errors on lagged, publicly observable firm characteristics. The resulting estimated coefficients are applied to current characteristics

[1] See, for example, Dugar and Nathan (1995), Das, Levine, and Sivaramakrishnan (1998), Lin and McNichols (1998), Michaely and Womack (1999), and Dechow, Hutton, and Sloan (2000).

[2] Overweighting is defined as investors weighting a signal in excess of the optimal Bayesian weights when forming expectations of future earnings. See Appendix A for more details.

to create a fitted prediction of future forecast errors. I show that the traditional approach can introduce biases into predicted forecast errors. Biases emerge whenever the observable firm characteristics used to predict forecast errors are correlated with unobservable inputs to analyst forecasts such as analysts' incentive misalignment or private information. Predicted forecast errors can be consistently above or below the realized forecast error depending on the sign and magnitude of these correlations. Moreover, biases in predicted forecast errors can vary across firms, limiting their ability to meaningfully sort stocks in the cross-section. Because tests of overweighting rely on sorting firms by predicted errors, it is difficult to assess whether investors overweight analyst forecasts without first making progress on a methodological front.

In this paper, I develop and implement a new approach to predicting analyst forecast errors that circumvents many of the problems hampering the traditional approach. This new approach also involves the use of historically estimated relationships but shifts the focus toward the prediction of future earnings and away from regression-based fitting of past forecast errors. I show that this approach is less sensitive to estimation bias and offers significant predictive power for realized forecast errors and future returns.

The methodology highlighted in this paper is referred to as the 'characteristic approach' to predicting analyst forecast errors. This title reflects the fact that I contrast analysts' earnings forecasts with 'characteristic forecasts' of earnings, where both forecasts are measured several months before firms' annual earnings announcements. I construct characteristic forecasts by fitting current earnings to the firm characteristics used by Fama and French (2000) in the prediction of future profitability: lagged earnings, book values, accruals, asset growth, dividends, and price. I estimate pooled cross-sectional regressions to capture large sample relations between earnings and lagged firm characteristics. I apply historically estimated coefficients to firms' most recent characteristics to create *ex ante* forecasts of future earnings. I first show that characteristic forecasts are an unbiased predictor of realized earnings and contrast these forecasts with those issued by sell-side analysts.

When contrasting characteristic and analyst forecasts, several interesting patterns emerge. First, firms with characteristic forecasts exceeding consensus analyst forecasts tend to have realized earnings that exceed the consensus, and vice versa. Second, when discrepancies exist, analysts subsequently revise their forecasts in the direction of characteristic forecasts leading up to earnings announcements. Third, analysts are more likely to raise buy/sell recommendations for a given firm when characteristic forecasts exceed the consensus analyst forecast, and vice versa. These results suggest that analysts are slow to incorporate the information embedded in characteristic forecasts when forecasting future firm performance and that overreliance on analyst forecasts may result in substantial valuation errors.

Given the potential for valuation errors when relying on analyst forecasts, I conduct a series of tests to examine whether investors overweight analyst forecasts. Using a simple two-period framework, I establish how researchers can precisely test for efficient market weights by relating future returns with differences between characteristic and analyst forecasts. To implement this test, I develop a new variable 'characteristic forecast optimism', defined as the *ex ante* characteristic forecast minus the prevailing consensus forecast, where higher values correspond to firms whose characteristics signal future earnings that exceed analyst projections. I document consistent abnormal returns to a strategy that buys firms in the highest quintile of characteristic forecast optimism and sells firms in the lowest quintile, consistent with investors systematically overweighting analyst forecasts and underweighting characteristic forecasts. This simple, unconditional quintile strategy generates average returns of 5.8% per year in out-of-sample tests.

Strategy returns significantly increase through contextual analysis and display a number of intuitive relations with firm characteristics and market trends. In conditional tests, returns increase to 9.4% per year among firms whose stock price is highly sensitive to earnings news. Similarly, characteristic forecast optimism is a stronger predictor of returns among small firms, firms with historically disappointing earnings, and firms with low financial transparency. These results are consistent with investors being more likely to overweight analyst forecasts among firms with poor information environments or when investors are uncertain about the mapping between current and future earnings. In intertemporal tests, characteristic forecast optimism is a stronger predictor of returns during high investor sentiment regimes, corresponding to periods when analysts face heightened incentives to bias forecasts.

An alternative explanation for these findings is that return predictability manifests in response to priced risk correlated with characteristic forecast optimism. To mitigate risk-based explanations, I demonstrate that return predictability is robust to Fama-French risk-adjustments and standard risk controls in cross-sectional tests. The ability of characteristic forecast optimism to predict returns is distinct from post-earnings announcement drift, momentum, the accrual anomaly, relative value strategies, and investor reliance on analysts' long-term growth forecasts. I also find that characteristic forecast optimism predicts subsequent earnings announcement returns, consistent with forecast discrepancies signaling earnings information that is not reflected in prices in a timely fashion.

Taken together, the magnitude and consistency of return prediction is striking in light of prior research concluding that investors efficiently weight analyst forecasts. The central implication of these findings is that investors fail to fully undo predictable biases in analyst forecasts and, as a result, distortions in analyst forecasts can influence the information content of prices. These findings suggest that regulators should not only be concerned with how distortions in analyst forecasts differentially impact the welfare of subsets of investors (e.g., retail vs. institutional) but also how they impact the efficient allocation of capital.

Two additional tests compare the characteristic approach to the traditional regression-based fittings of past forecast errors. First, I fit past forecast errors to the same firm characteristics used when constructing characteristic forecasts and demonstrate that the characteristic approach significantly outperforms the traditional approach in predicting analyst forecast errors, forecast revisions, and future returns. Second, I compare the predictive power of characteristic forecast optimism to two existing forecast error prediction models and again find evidence favoring the use of the characteristic approach.

2. Motivation

This section highlights methodological concerns associated with the traditional approach to predicting analyst forecast errors and provides an overview of the characteristic approach developed in this paper. To begin, suppose that firm j's realized earnings in year t, $E_{j,t}$, can be written as a function of observable firm characteristics:

$$E_{j,t} = \sum_{i=1}^{M} \beta_i \cdot X_{i,j,t-1} + \epsilon_{j,t} \tag{1}$$

where $X_{1,j,t-1}...X_{M,j,t-1}$ denote a comprehensive set of M firm characteristics associated with the firm's earnings that are publicly observable in t-1 and $\epsilon_{j,t}$ denotes the component of realized earnings not predicted by $X_{1,j,t-1}...X_{M,j,t-1}$. Similarly, suppose that in year t-1 analyst forecasts of year t earnings are given as:

$$AF_{j,t-1} = \sum_{i=1}^{M} \gamma_i \cdot X_{i,j,t-1} + \sum_{i=1}^{K} \delta_i \cdot Z_{i,j,t-1} + \eta_{j,t-1} \tag{2}$$

where analysts also have access to public signals $X_{1,j,t-1}...X_{M,j,t-1}$, and $Z_{1,j,t-1}...Z_{K,j,t-1}$ denote analysts' private information and incentives to bias forecasts. This representation of analyst forecasts is motivated by a substantial literature documenting the role of competing interests in shaping analyst outputs (see Section 3 for further discussion). For example, Z_i may denote private information obtained from firms' management or pressure from analysts' employers to issue favorable forecasts. Combining (1) and (2), realized forecast errors equal:

$$FE_{j,t} \equiv E_{j,t} - AF_{j,t-1} = \sum_{i=1}^{M} (\beta_i - \gamma_i) \cdot X_{i,j,t-1} + \epsilon_{j,t} - \sum_{i=1}^{K} \delta_i \cdot Z_{i,j,t-1} - \eta_{j,t-1} \tag{3}$$

Next, consider the traditional approach of predicting analyst forecasts errors.[3] In the first step, the researcher regresses realized forecast errors, $FE_{j,t}$, on lagged publicly observable

[3]For examples of the traditional approach, see Ali, Klein, and Rosenfeld (1992), Elgers and Murray (1992), Lo and Elgers (1998), Frankel and Lee (1998), Gode and Mohanram (2009), and Hughes, Liu, and Su (2008).

firm characteristics, $X_{1,j,t-1}...X_{M,j,t-1}$. Equation (3) demonstrates that the error from this regression equals:

$$\Omega_{j,t} \equiv \epsilon_{j,t} - \sum_{i=1}^{K} \delta_i \cdot Z_{i,j,t-1} - \eta_{j,t-1} \quad (4)$$

The fact that the regression error is a function of analysts' private information or incentives, $Z_{i,j,t-1}$, suggests that the estimated values of $(\beta_i - \gamma_i)$ in equation (3) are subject to bias. The following example highlights the source of this bias. Existing studies commonly include analysts' long-term growth forecasts as a control variable when estimating equation (3). Whenever analysts' incentives influence their long-term growth forecasts, the regression error, $\Omega_{j,t}$, becomes correlated with the set of control variables, $X_{i,j,t-1}$. At the same time, there is reason to expect that $\Omega_{j,t}$ is also correlated with analyst forecast errors, $FE_{j,t}$. Several studies argue that brokerage firms provide analysts with incentives to bias their earnings forecasts in response to an implicit *quid pro quo* arrangement with firms' management (e.g., Dugar and Nathan (1995), Lin and McNichols (1998)). Thus, $\Omega_{j,t}$ may be negatively correlated with $FE_{j,t}$ if analysts' incentives make them more likely to appease firm management by issuing high earnings forecasts. In contrast, $\Omega_{j,t}$ may be positively correlated with $FE_{j,t}$ if analysts' incentives make them more likely to appease firm management by creating beatable earnings targets. Regardless of the signs of these correlations, the fact that $\Omega_{j,t}$ is correlated with $FE_{j,t}$ and $X_{i,j,t-1}$ indicates the presence of correlated omitted variable bias. Both scenarios result in biased coefficients when estimating equation (3), although the direction of the bias is unclear *ex ante* and can vary across firms and time.

In the second step of the traditional approach, the researcher applies historically estimated values of $(\beta_i - \gamma_i)$ to current firm characteristics, $X_{i,j,t}$. The resulting fitted value equals the researcher's prediction of the year t+1 analyst forecast error:

$$\widehat{FE}^{T}_{j,t+1} = \sum_{i=1}^{M} (\widehat{\beta_i - \gamma_i}) \cdot X_{i,j,t} \quad (5)$$

where the T-superscript indicates that the predicted forecast error is calculated under the traditional approach. Note that the use of biased regression coefficients results in a predicted analyst forecast error that does not equal the expected value of the realized forecast error:

$$(\widehat{\beta_i - \gamma_i}) \neq \mathbf{E}_t[(\beta_i - \gamma_i)] \Rightarrow \widehat{FE}^T_{j,t+1} \neq \mathbf{E}_t[FE_{j,t+1}] \tag{6}$$

where $\mathbf{E}_t[\cdot]$ denotes the time t expectations operator with respect to the researcher's information set, which does not include analysts' private information or incentives. $\widehat{FE}^T_{j,t+1}$ may be predictably above or below the realized forecast error depending on the sign and magnitude of bias in the first stage estimated coefficients, $(\widehat{\beta_i - \gamma_i})$. The amount of bias can vary across firms and time, which casts doubt on the ability of predicted forecast errors to meaningfully sort multiple stocks in the cross-section.

As noted above, bias in the estimated coefficients results from researchers' inability to observe inputs to analyst forecasts, denoted by $Z_{i,j,t-1}$ in equation (2). Thus, it may be initially tempting to conclude that researchers can avoid these biases by controlling for analysts' incentives and private information, such as analysts' affiliations with the covered firm as in Lin and McNichols (1998). The problem with this conclusion is that it is generally impossible for the reseacher to identify all inputs influencing analyst forecasts. Moreover, even if researchers were able to develop a comprehensive set of proxies for $Z_{i,j,t-1}$, these proxies would almost certainly measure the underlying inputs with error. As a result, when controlling for these proxies, the coefficients from estimating equation (2) would be subject to the concern that the sign and magnitude of coefficient biases are generally unknown when there is more than one variable in a multivariate regression subject to measurement error (Rao (1973)). Thus, attempting to control for unobservable inputs may have the unintended effect of exacerbating the bias.

To circumvent biases stemming from the traditional approach, I propose the use of the characteristic approach to predicting analyst forecast errors. A crucial difference between the characteristic and traditional approaches is that instead of regressing realized forecast errors on firm characteristics, the characteristic approach directly estimates future earnings by empirically estimating equation (1):

$$\hat{E}_{j,t+1} = \sum_{i=1}^{M} \hat{\beta}_i \cdot X_{i,j,t} \tag{7}$$

A benefit of this approach is that, under mild distributional assumptions, the resulting earnings forecast is an unbiased estimate of future earnings such that $\hat{E}_{j,t+1} = \mathbf{E}_t[E_{j,t+1}]$.[4] Next, I predict forecast errors by contrasting $\hat{E}_{j,t+1}$ with the publicly observable analyst forecast of t+1 earnings. Using the characteristic approach, predicted analyst forecasts errors satisfy the following property:

$$\widehat{FE}^{C}_{j,t+1} = \hat{E}_{j,t+1} - AF_{j,t} = \mathbf{E}_t[E_{j,t+1} - AF_{j,t}] = \mathbf{E}_t[FE_{j,t+1}] \tag{8}$$

where the C-superscript denotes the predicted forecast error calculated using the characteristic approach. In contrast to traditional approaches, the characteristic approach results in unbiased estimates of the realized analyst forecast error.

The main takeaway from this section is that the traditional approach to predicting analyst forecast errors results in biased estimates that may be above or below the realized forecast error. The direction and magnitude of the bias depends on the correlation between the observable firm characteristics used to predict analyst forecast errors and unobservable inputs to analyst forecasts. I show that this bias is largely avoidable using the characteristic approach, which shifts the focus to the prediction of future earnings. Section 3 discusses the motivation for the characteristic approach in the context of the existing literature, Section 4 discusses the empirical implementation of the characteristic approach, and Section 5 contrasts the predictive power of each approach.

[4]The unbiasedness of $\hat{E}_{j,t+1}$ assumes that earnings do not systematically reflect unobservable components, such as managerial skill or effort, correlated with the observable firm characteristics, $X_{1,j,t-1}...X_{M,j,t-1}$. If this assumption is not certain to hold, both approaches may result in biased predicted forecast errors though the likelihood of correlated omitted variable bias remains higher for the traditional approach. Section 4 provides empirical evidence that $\hat{E}_{j,t+1}$ is generally unbiased.

3. Relation to literature

This study relates to three primary streams of literature. The first stream of literature documents that the information that analysts provide significantly influences the market's assessment of firm value. A second steam provides evidence that analysts' incentives diverge from those of the end users of the earnings forecasts resulting in biased forecasts of firm performance. Motivated by this incentive misalignment, a third stream of literature tests whether investors rationally anticipate and undo the predictable bias in analyst-based signals. This paper provides a link between these streams of literature by examining the predictability of future analyst errors and whether investors systematically overweight analyst forecasts.

Security analysts play an important role as information intermediaries between firms and investors. Consistent with this view, several studies document that security prices move in the direction of forecast revisions and recommendation changes (e.g., Givoly and Lakonishok (1979), Lin and McNichols (1998), Clement and Tse (2003), Ivkovic and Jegadeesh (2004), Jegadeesh et al. (2004), Frankel, Kothari, and Weber (2006), Kirk (2011)). The tendency for prices to respond to changes in analyst forecasts indicates that these forecasts play a significant role in the development of earnings expectations and the price discovery process.

The usefulness of analysts' recommendations and forecasts for investment decisions, however, is limited by several potential biases. For example, McNichols and O'Brien (1997), Lin and McNichols (1998), and Hong and Kubik (2003) document that analysts face incentives to provide overly optimistic forecasts and recommendations to secure lucrative investment banking relationships. Similarly, Francis and Philbrick (1993), Lim (2001), and Libby et al. (2008) demonstrate that analysts' desire for information and access to management result in biased forecasts and recommendations. Additional studies indicate that biases result from analysts' incentives to generate trading revenue and institutional clientele (e.g., Hayes (1998), Irvine (2004), Groysberg, Healy, and Maber (2011)), asymmetric responses to negative and positive news (e.g., Easterwood and Nutt (1999)), underreaction to past news (e.g., Abarbanell (1991), Mendenhall (1991), Ali, Klein, and Rosenfeld (1992)), over-extrapolation of past trends (e.g., Bradshaw (2004)), and the overweighting of private information (Chen and Jiang (2006)). Collectively, this literature finds that ignoring predictable biases in analyst forecasts and recommendations can lead to significant valuation errors.[5]

Given the potential for misvaluation, several studies seek to determine how investors use the information that analysts provide when forming performance expectations. For example, Mikhail, Walther, and Willis (2007) and Malmendier and Shanthikumar (2007) document that smaller investors tend to lose money by trading in accordance with analyst recommendations. Although their findings indicate that subsets of investors overweight analyst-based signals, they do not provide evidence of *systematic* overweighting because they also establish that larger investors tend to profit from trading against analyst recommendations.

La Porta (1996) documents a negative relation between analyst long-term growth forecasts and future returns, which is consistent with investors systematically overweighting analyst projections of earnings growth. However, Dechow and Sloan (1997) demonstrate that the value/glamour effect accounts for a significant portion of the returns associated with long-term growth forecasts. Similarly, Da and Warachka (2011) find that long-term growth forecasts fail to predict returns when controlling for past returns and analyst forecast dispersion. In fact, Da and Warachka (2011) find that comparing short- and long-term growth forecasts predicts revisions in the latter and concludes that investors underweight the information content of analyst growth forecasts.

A related stream of research documents a robust tendency of prices to drift for several weeks in the direction of past analyst recommendation revisions (e.g., Givoly and Lakonishok (1979), Mendenhall (1991), Stickel (1991), Gleason and Lee (2003), Barth and Hutton

[5]The idea that investors ignore predictable analyst errors is directly related to existing papers documenting that security prices fail to fully reflect large sample properties of earnings and earnings changes. For example, Ou and Penman (1989) and Piotroski (2000), find that financial ratios carry predictive power for earnings changes that are not immediately reflected in prices. Similarly, Sloan (1996) finds that prices behave as if investors fixate on total reported earnings, failing to recognize that firms with high accrual components of earnings underperform in the future and Lakonishok, Shleifer, and Vishny (1994) provide evidence that investors overestimate future earnings growth differences between glamour and value firms.

(2004), Ivkovic and Jegadeesh (2004), Jegadeesh et al. (2004)). Similarly, Womack (1996) and Barber et al. (2001) demonstrate that the returns of firms with the most favorable recommendations outperform those with the least favorable recommendations. Frankel and Lee (1998) documents that differences between price and estimates of firm value derived from analyst forecasts predict future abnormal returns. These studies collectively suggest that investors do not fully utilize the information content of analysts' pronouncements in a timely fashion. The tendency of prices to drift in the direction of analyst signals until confirmatory news is released is consistent with investors systematically underweighting analyst revisions and overweighting firms' share price. Thus, taken together, the literature provides mixed evidence regarding how investors weight analyst-based signals.

This paper differs from many of the above studies by focusing on predictable errors with respect to earnings forecasts rather than buy/sell recommendations or growth projections. Focusing on earnings forecasts offers three important benefits. First, analyst errors with respect to earnings forecasts are easier to measure relative to buy/sell recommendations or growth forecasts. Measurability facilitates a comparison of the magnitude of analyst errors and revisions in investors' expectations. Intuitively, if investors overweight analyst forecasts, mispricing should be proportional to the magnitude of the predictable analyst error. Thus, focusing on analyst forecast errors contributes to more precise tests of how investors weight the information that analysts provide. (see Appendix A and Section 4 for more details). Second, analyst earnings forecasts are more widely available than recommendations or growth projections, thus permitting tests of market weighting for a broader sample of firms. Third, analyst earnings forecast errors are publicly observable within a relatively shorter period of time, which makes tests of overweighting less sensitive to research design problems such as survivorship or omitted variable biases that may drive variation in the measurement of analyst errors and returns.

In designing tests of how investors weight analyst forecasts, this study relates to the literature demonstrating that analyst earnings forecast errors are predictable using publicly available signals.[6] For example, Ali, Klein, and Rosenfeld (1992), Elgers and Lo (1994), Lo and Elgers (1998), Gode and Mohanram (2009), and Konchitchki et al. (2011) use the traditional approach to create predicted analyst forecast errors and demonstrate that analysts underreact to publicly observable signals.

Similarly, Frankel and Lee (1998) and Hughes, Liu, and Su (2008) use firm characteristics to predict future analyst forecast errors with an eye toward identifying potential mispricing. Frankel and Lee (1998) fit realized two-year ahead forecast errors to firm characteristics including book-to-price, sales growth, and analysts long-term growth forecasts.[7] They find that a strategy of buying firms in the highest quintile of predicted two-year ahead forecast errors and selling firms in the lowest quintile generates mixed evidence of one-year ahead return predictability but produces statistically significant abnormal returns over long-window horizons. In contrast, Hughes, Liu, and Su (2008) find that although analyst forecast errors are predictable, investment strategies aimed at exploiting the predictable component do not generate abnormal returns.[8] Based on these findings, Hughes, Liu, and Su (2008) conclude that investors efficiently weight analyst forecasts and, thus, that market prices reflect the predictable component of analyst errors. The evidence that I present in this paper suggests that the absence of a link between predicted forecast errors and future returns in Hughes, Liu, and Su (2008) is an artifact of their methodology, which can result in unnecessary noise in their estimates of predicted analyst forecast errors.

[6] A related literature combines alternative earnings forecasts to improve estimates of future earnings such as Conroy and Harris (1987) and Lobo and Nair (1990) who find that combining analyst and statistical forecasts improve forecast accuracy.

[7] The adjustment of analyst forecasts is also commonly used to estimate implied cost of capital. See Easton and Sommers (2007) and Hou, van Dijk, and Zhang (2011) for discussions of this practice.

[8] One methodological difference between Frankel and Lee (1998) and Hughes, Liu, and Su (2008) that may help to explain their differening conclusions is that the former paper focuses on two-year-ahead forecasts whereas the latter focuses on one-year-ahead forecasts. This difference is potentially important because prior research establishes that analysts' incentives to upwardly bias forecasts (e.g., generating trading volume or investment banking business) play a larger role in determining two-year-ahead forecasts compared to shorter horizon forecasts. You (2011) argues that two-year-ahead forecast optimism is more strongly influenced by these incentives because analysts are rarely compensated based on the accuracy of their longer horizon forecasts. To the extent that the correlation between analysts' incentives and two-year-ahead forecast bias display lower cross-sectional variation than the correlation with one-year-ahead forecasts, applying the traditional approach to two-year-ahead forecasts may yield greater predictive power for future cash flow news by reducing noise in cross-sectional rankings.

4. Empirical tests

4.1. Estimating Characteristic Forecasts and Sample Selection

As outlined in Section 2, the characteristic approach to predicting analyst forecast errors involves comparing analyst forecasts to characteristic forecasts estimated from past firm characteristics. The process of calculating characteristic forecasts mimics the construction of $\hat{E}_{j,t+1}$ in equation (7) and follows closely from the procedures developed in Fama and French (2006) and Hou, van Dijk, and Zhang (2011).

Creating characteristic forecasts requires selecting a set of firm characteristics used in the prediction of future earnings. Any publicly observable firm characteristic may be used and, hence, there is an infinite set of possible permutations. To avoid arbitrarily selecting a set of firm characteristics, I rely on the firm characteristics, appropriately scaled, used by Fama and French (2006) in the prediction of future profitability. More specifically, I estimate the following cross-sectional regression for all firms reporting earnings in calendar year t:

$$\begin{aligned} E_{j,t} =& \beta_0 + \beta_1 E_{j,t-1} + \beta_2 NEGE_{j,t-1} + \beta_3 ACC^{-}_{j,t-1} + \beta_4 ACC^{+}_{j,t-1} + \beta_5 AG_{j,t-1} \\ &+ \beta_6 DD_{j,t-1} + \beta_7 DIV_{j,t-1} + \beta_8 B/M_{j,t-1} + \beta_9 Price_{j,t-1} + \epsilon_{j,t-1} \end{aligned} \tag{9}$$

where the subscripts indicate that earnings are regressed on lagged characteristics. E_j is defined as a firm's earnings per share if earnings are non-negative (described more below), a binary variable indicating negative earnings ($NEGE_j$), negative and positive accruals per share (ACC^{-}_j, ACC^{+}_j) where accruals equal the change in current assets [Compustat item ACT] plus the change in debt in current liabilities [Compustat item DCL] minus the change in cash and short-term investments [Compustat item CHE] and minus the change in current liabilities [Compustat item CLI], the percent change in total assets (AG_j), a binary variable indicating zero dividends (DD_j), dividends per share (DIV_j), book-to-market (B/M_j) defined as book value scaled by market value of equity, and end-of-fiscal-year share price ($Price_j$).[9]

The dependent variable in equation (9) is a firm's earnings per share ($E_{j,t}$). Philbrick and Ricks (1991) and Bradshaw and Sloan (2002) note that IBES earnings and analyst earnings forecasts often omit non-recurring items that are included in GAAP earnings. Bradshaw and Sloan (2002) notes that special items account for most of the discrepancies between the two earnings numbers. To facilitate a comparison between characteristic and analyst forecasts, I use net income before extraordinary items and substract firms' special items multiplied by 0.65, where the 0.65 reflects an assumed tax rate of 35% as in Bradshaw and Sloan (2002).

Prior research employs firm-specific time-series models to forecast future quarterly earnings (e.g., Foster (1977), Watts and Leftwich (1977), and O'Brien (1988)). I employ cross-sectional characteristic forecasts instead of time-series forecasts for three reasons. First, time-series forecasts commonly assume that earnings follow an ARIMA structure. This approach significantly restricts the available sample by requiring sufficient historical data to estimate the parameters of the firm-specific ARIMA structure. Characteristic forecasts of year t+1 earnings require only firm-specific information for year t and, thus, the analysis incorporates a much larger sample of firms. Second, time-series forecasts display lower levels of accuracy relative to analyst forecasts (e.g., Brown et al. (1987) and O'Brien (1988)), potentially limiting their ability to serve as a benchmark along which analyst forecasts can be judged. Finally, cross-sectional forecasts incorporate additional characteristics such as firms' accruals and dividends that provide incremental explanatory power for future profitability (e.g., Fama and French (2006) and Hou, van Dijk, and Zhang (2011)).

I estimate equation (9) for each firm-year in Compustat possessing non-missing values of the nine characteristics. Panel A of Table 1 presents average annual coefficients from fitting one-year ahead (denoted as 'FY1') earnings using equation (9). The regression coefficients indicate that firms with higher past earnings and dividends, non-loss firms, firms with low

[9] In Section 5.2, I discuss the results of estimating variants of equation (9) that exclude characteristics involving price and use a continuous version of earnings as well as an extended model that also uses analyst forecasts to predict future earnings. Similarly, I also estimate the earnings forecast model of Hou, van Dijk, and Zhang (2011). These variations lead to qualitatively similar results.

income increasing accruals and asset growth, and firms with higher share prices tend to have higher future earnings. The average adjusted R^2 is 0.561 indicating that this approach explains a substantial portion of cross-sectional variation in FY1 earnings.

After estimating equation (9), I apply historically estimated coefficients to current firm characteristics such that characteristic forecasts are available on an *ex-ante* basis, prior to observing realized FY1 earnings. The year t characteristic earnings forecast for firm j equals:

$$\begin{aligned} CF_{j,t} \equiv & \hat{\beta}_0 + \hat{\beta}_1 E_{j,t} + \hat{\beta}_2 NEGE_{j,t} + \hat{\beta}_3 ACC^-_{j,t} + \hat{\beta}_4 ACC^+_{j,t} + \hat{\beta}_5 AG_{j,t} \\ & + \hat{\beta}_6 DD_{j,t} + \hat{\beta}_7 DIV_{j,t} + \hat{\beta}_8 B/M_{j,t} + \hat{\beta}_9 Price_{j,t} \end{aligned} \tag{10}$$

where $\hat{\beta}$ denotes the coefficients obtained from estimating (9) in year t-1 and $CF_{j,t}$ measures the characteristic forecast of year t+1 earnings.

After calculating characteristic forecasts, I create a sample at the intersection of Compustat and IBES. The IBES sample consists of all firm-years for which there exist FY1 earnings and long-term-growth (LTG) consensus forecasts in the IBES Unadjusted Summary file within the three months prior to the portfolio formation date.[10] I use the IBES Unadjusted file because the IBES Adjusted file reflects earnings estimates that are *retroactively* adjusted for stock splits (Baber and Kang (2002), Payne and Thomas (2003)). Because stock splits tend to follow from strong firm performance, failure to undo *ex post* split adjustments can result in look-ahead bias and a spurious positive relation between forecast differences and subsequent returns.

Recall from Section 2 that predicted forecast errors calculated under the characteristic approach equal the level of earnings predicted by past firm characteristics (i.e., $\hat{E}_{j,t+1}$) minus the analyst forecast. Also note that the characteristic forecast described by equation (10) mirrors the construction of $\hat{E}_{j,t+1}$. Thus, motivated by equations (7) and (8), my empirical

[10]Requiring an FY1 and LTG IBES forecast raises concerns that the firms in the sample used to estimate equation (9) significantly differ from the IBES analyst sample. In untabulated results, I find that estimating equation (9) only on the set of firms with FY1 and LTG forecasts does not materially affect the results of the main empirical tests.

prediction of the concensus forecast error equals the difference between the characteristic and analyst forecasts. Specifically, I create a new variable 'characteristic forecast optimism' ($\mathrm{CO}_{j,t}$) that I use as the primary means of ranking firms in cross-sectional tests. $\mathrm{CO}_{j,t}$ is defined as the characteristic forecast of FY1 earnings per share minus the prevailing FY1 forecast in IBES and scaled by total assets per share:

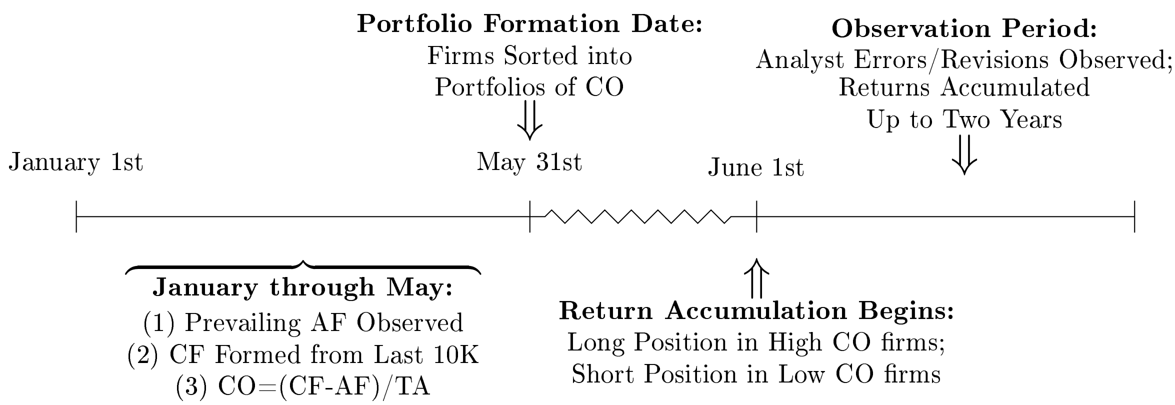
$$CO_{j,t} = \frac{CF_{j,t} - AF_{j,t}}{TA_{j,t}} \tag{11}$$

where the numerator is equivalent to $\widehat{FE}^{W}_{j,t+1}$ in equation (8) and $TA_{j,t}$ denotes firm j's total assets per share in year t. To ensure that characteristic and analyst earnings forecasts are reported on the same share basis, I use characteristic forecasts of earnings in terms of the number of shares outstanding on the date that the IBES consensus forecast is observed, as reported in CRSP.[11] I scale the difference between characteristic and analyst forecasts by total assets rather than equity prices because, to the extent that equity prices reflect earnings expectations created by analyst forecasts, the numerator and denominator of CO may move in tandem, which can potentially induce spurious cross-sectional variation (Ball (2011), Cheong and Thomas (2011)).[12]

I merge the intersection of the Compustat and IBES databases with monthly return data from CRSP assuming that firms' financial statements are available exactly five months following the fiscal year end. I refer to this date as the 'portfolio formation date' reflecting the point in time at which I assume all information needed to assign firms to tradable portfolios is publicly observable. The diagram below provides the timeline of analysis for an example firm with a December 31st fiscal year end:

[11] For example, suppose that equation (9) is estimated where total earnings is scaled by 2 million, the number of shares outstanding reported in Compustat, and that the number of shares outstanding on the date of the unadjusted IBES consensus forecast is 3 million. In this example, I multiply the characteristic earnings forecast by two-thirds to ensure that both forecasts are on the same share basis. Similar results obtain when using the IBES Detail Unadjusted File in place of the IBES Unadjusted Summary file.

[12] Similar concerns emerge from the use of prices in forecasting future earnings. Section 5 discusses additional tests that remove the link between characteristic forecasts and price.



The above diagram uses firms with December 31st fiscal year ends as an example to emphasize that the empirical tests are constructed to avoid look ahead biases: all of the signals used for prediction are known prior to May 31st and all of the outcomes being predicted are observed after June 1st. Enforcing a minimum five-month separation between firms' fiscal year end and portfolio formation date is conservative, thus reducing concerns of look-ahead bias when forming investment portfolios. The five-month separation also raises the likelihood that the information used to create characteristic earnings forecasts is a subset of the information available to analysts at the portfolio formation date. This mitigates concerns that analyst forecast errors are predictable because analysts do not yet have access to the information used in constructing characteristic forecasts.

Throughout the analysis, I eliminate financial firms with SIC codes between 6000 and 6999. I require firms to have six months of prior return data to calculate return momentum and eliminate firms with a share price below \$5 to mitigate microstructure-related problems such as bid-ask bounce. To avoid delisting biases when using CRSP data, I calculate delisting returns in accordance with Shumway (1997) and Beaver, McNichols, and Price (2007).

The final sample consists of 51,591 firm-years spanning 1980-2009. Figure 1 presents observation counts for each sample year. The number of firms varies from a low of 546 firms in 1980 to a high of 2,656 firms in 2007. The figure also contains median analyst and characteristic forecasts per year. The median analyst forecast is generally above the median characteristic forecast, consistent with analysts facing incentives to issue optimistic forecasts.

Panel B of Table 1 provides the average annual Pearson correlations for the final sample between characteristic forecasts, analyst forecasts, and the realized FY1 earnings number reported in Compustat, adjusted for special items, denoted by 'RE'. The correlation between CF and AF is 0.851, consistent with characteristic and analyst forecasts being highly, but not perfectly, correlated. Although both characteristic and analyst forecasts are strongly correlated with realized earnings, the Pearson correlation between AF and RE (0.778) is larger than the correlation between CF and RE (0.729).

Panel B also provides average annual forecast errors per share and corresponding t-statistics. For each calendar year, I calculate the average difference between realized earnings and the two earnings forecasts. I report the time-series average difference over the 30-year sample period. The average characteristic forecast error per share is 0.112 (t-statistic=1.587), which is consistent with the average difference between realized and forecasted earnings being insignificantly different than zero. In contrast, the average analyst error is -0.216 (t-statistic=-4.846), which is consistent with the average analyst forecast being overly optimistic.

Panel C of Table 1 presents regression results from a pooled estimation of earnings regressed on CF and AF. Column (1) reports the results from regressing realized earnings on CF. The characteristic forecast coefficient is 1.001 (t-statistic=19.78). To control for cross-sectionally and time-series correlated errors, all regression t-statistics are based on standard errors two-way cluster adjusted by industry and year (Petersen (2009), Gow, Ormazabal, and Taylor (2010)). An F-test fails to reject the null hypothesis that the CF coefficient equals one, consistent with CF being an unbiased measure of future earnings (p-value=0.862). The positive intercept in column (1), however, is unexpected and consistent with the realized earnings exceeding characteristic forecast by a positive constant. Column (2) contains the results from regressing realized earnings on AF. The analyst forecast coefficient is 1.054 (t-statistic=42.27). The significantly negative intercept is consistent with the results in Panel B that analysts tend to issue overly optimistic earnings forecasts. Column (3) demonstrates that both characteristic and analyst forecasts have positive and significant coefficients when fitting realized earnings. This result suggests that both forecasts are incrementally useful in predicting realized earnings and that the optimal forecast of earnings uses information from both forecasts. The F-test of equal coefficients on CF and AF in column (3) is also rejected. Mirroring the large t-statistic differences across columns (1) and (2), the coefficient on AF exceeds the coefficient on CF suggesting that the optimal forecast places larger weight on analyst forecasts compared to characteristic forecasts.

4.2. Predicting Realized Forecast Errors and Forecast Revisions

Panel A of Table 2 contains mean descriptive statistics across quintiles of characteristic forecast optimism, CO. The first and second columns of Panel A contain the two main components of CO, characteristic forecasts and analyst forecasts per share. The bottom of each column contains the difference between the highest and lowest quintile of CO as well as the p-value for the high-low differential. The p-values corresponding to the null hypothesis of no difference across the high and low CO quintiles are based on the 30-year time-series average difference over the 1980-2009 sample window. Although characteristic forecasts are significantly different across the extreme quintiles of CO the same is not true for analyst forecasts. SIZE, defined as the log of market capitalization, is insignificantly different across the high and low CO quintiles. LBM, defined as the log of the firm's book-to-market ratio, is higher for high CO firms which is consistent with the negative relation between earnings and book-to-market shown in Panel A of Table 1.

Panel B of Table 2 contains descriptive statistics of analyst forecast errors. BIAS equals the difference between earnings as reported in Compustat and the prevailing consensus forecast, scaled by total assets per share. I calculate the median value of BIAS each year and report the median and mean of the annual time-series. The median is monotonically increasing across CO quintiles, consistent with forecast differences helping to predict analyst errors. The mean is generally increasing across CO quintiles but lacks monotonicty in the upper tail, consistent with the findings of Easterwood and Nutt (1999) and Chen and Jiang (2006) that analysts more efficiently impound good news into their forecasts than bad news. Panel B also contains the percentage of firm-years for which (i) realized earnings is less than the analyst forecast and (ii) realized earnings are greater than the analyst forecast. Comparing each forecast against realized earnings provides an indication of the ratio of positive to negative forecast errors and conforms to the call in Abarbanell and Lehavy (2003) for non-parametric characterizations of forecast errors. The results show that when CO is low, earnings tend to be below the analyst forecast and, when CO is high, earnings tend to be above the analyst forecast. Note that the percentage of observations with earnings above (below) the analyst forecast monotonically increases (decreases) across CO quintiles, indicating that discrepancies between characteristic and analyst forecasts help to predict the frequency of positive and negative analyst forecast errors.

Table 3 examines the relations between CO and BIAS in a multivariate regression. Note that regressing forecast errors on firm characteristics likely results in biased regression coefficients as outlined in Section 2, so the resulting coefficients should be interpreted with caution. However, this analysis is designed to demonstrate that CO possesses incremental explanatory power for forecast errors and not to create a fitted value of the forecast error. To more closely mimic the portfolio approach in Table 2, all control variables are sorted into quintiles each year, where the highest (lowest) quintile assumes a value of one (zero).

Panel A presents the results from regressing realized analyst forecast errors, BIAS, on CO as well as firm-specific controls. ACC equals total accruals scaled by total assets. I control for accruals because Sloan (1996) finds that firms with a high accrual component of earnings underperform in terms of future earnings and returns relative to low accrual firms. LTG is obtained from IBES as the consensus long-term growth rate forecast. Following Gebhardt, Lee, and Swaminathan (2001), when the long-term growth forecast is not available, LTG is set equal to the growth rate implicit in the consensus FY1 and FY2 earnings forecasts as reported in IBES. As in Frankel and Lee (1998), I control for firms' book-to-market ratio and long-term growth rate forecast as proxies for analyst optimism. Finally, I control for momentum to mitigate concerns that the predictability of forecast errors is attributable to prices leading earnings news. MOMEN is the market-adjusted return over the six months prior to the portfolio formation.

The first column of Panel A contains results from regressing BIAS on the main control variables. BIAS is negatively related to accruals and long-term growth forecasts and positively related to a firm's size and momentum. Column (2) presents the results from adding CO to the regression. The coefficient on CO is positive and statistically significant, consistent with the characteristic approach offering explanatory power for forecast errors incremental to standard controls. Note that CO appears to have a stronger relation with BIAS than the other control variables (as indicated by t-statistics). To mitigate concerns that analysts are forecasting a different earnings number than the earnings reported in Compustat adjusted for special items, I also calculate an alternative measure of analyst forecast errors, IBIAS, defined as the realized EPS reported in IBES minus the June 30th consensus forecast, and scaled by total assets per share.[13] Columns (3) and (4) of Panel A contain qualitatively similar results where IBIAS is the dependent variable.

Panel B of Table 3 contains the regression results where the dependent variables measure revisions in analyst forecasts and recommendations. REV equals the change in the consensus forecast from the portfolio formation date to the actual earnings announcement date and scaled by total assets per share. Similarly, IMB equals the average difference in the number of upward and downward buy/sell revisions, scaled by the number of revisions during the window between the portfolio formation date and the firm's earnings announcement. IMB is coded such that higher values correspond to increased buy recommendations relative to sell recommendations. Columns (1) and (2) contain the results associated with REV. The coefficient on CO is positive and significant indicating that analysts tend to revise their

[13] I do not use IBIAS as the main outcome variable because the IBES reported realized EPS is missing for approximately 10% of my final sample. Similarly, Hong and Kacperczyk (2010) compare analyst forecasts with Compustat earnings and cite significant data errors in reported IBES earings. Thus, I use BIAS as the main dependent variable to maximize the sample size available for my main tests.

forecasts in the direction of characteristic forecasts leading up to the announcement. Columns (3) and (4) display regression results associated with IMB. The coefficient on CO is again incrementally positive and significant, indicating that analysts are slow to incorporate the information content of characteristic forecasts into their recommendations.

To summarize the results up to this point, I find that characteristic forecasts are a generally unbiased measure of realized earnings and that differences between characteristic earnings and analyst forecasts predict analyst forecast errors, forecast revisions, and changes in buy/sell recommendations. To the extent that analyst forecast errors and revisions convey earnings news to the market, these findings suggest that failing to recognize the predictable component of forecast errors and revisions may result in predictable risk-adjusted returns.

4.3. The Relation between Characteristic Forecast Optimism and Future Returns

Do investors systematically overweight analyst forecasts? Answering this question requires first designing empirical tests that precisely define and identify the overweighting and underweighting of distinct earnings forecasts. In Appendix A, I use a simple two-period framework to show how researchers can test for efficient market weights by relating future returns and differences between characteristic and analyst forecasts.[14] Specifically, returns from a long-short strategy that sorts firms by forecast differences provides a means of assessing the weight that investors allocate to each forecast. Intuitively, a reliably positive return to a strategy that buys firms with high CO and sells firms with low CO would provide evidence that investors systematically overweight analyst forecasts and underweight characteristic forecasts relative to the optimal Bayesian weights.

To test for evidence of overweighting, Panels A and B of Table 4 provide average realized returns for each CO quintile. Panel A presents average raw returns denoted by RR(X,Y),

[14] Within the simple framework outlined in Appendix A, the conclusion that investors overweight analyst forecasts is reached if there exist at least one alternative earnings forecast for which discrepancies between the alternative and analyst forecasts predict future returns. Thus, a sufficient condition to establish that investors overweight analyst forecasts is to find a single forecast that satisfies this criteria. Though the main tests rely on characteristic forecasts specified by equation (10), Section 5.2 discusses the robustness of the paper's main findings to alternative earnings forecast models.

which equal the corresponding cumulative return accumulated from month X to month Y following the portfolio formation date. For December fiscal year end firms, portfolios are formed at the conclusion of May and thus RR(1,12) corresponds to the cumulative raw return from the beginning of June until the end of May of the following year. Market-adjusted returns are defined analogously and denoted by RET(X,Y).

Panel A of Table 4 demonstrates that one-year ahead raw returns, RR(1,12), monotonically increase across CO quintiles. The long-short CO strategy results in average raw returns of 5.8% in the first year following portfolio formation. t-statistics for the null hypothesis of equal returns across the highest and lowest quintiles of CO are based on Monte Carlo simulations. For each year of the 1980-2009 sample, I form empirical reference distributions that randomly assign all firms to quintiles by matching the observational counts in each CO quintile. I simulate 1,000 portfolios for each year and calculate the average long-short difference for each simulated portfolio. The aggregation of the simulated long-short returns form the empirical reference distributions, resulting in annual estimates of the mean and standard deviation of the strategy return under the null hypothesis. I calculate and report average bootstrap t-statistics by contrasting the realized annual hedge returns against the empirical reference distributions. This approach avoids look-ahead bias because the reference portfolios consist of only those firms that were available at the time the CO portfolios are formed. Similarly, the use of bookstrap t-statistics mitigates concerns of skewness bias raised by Kothari and Warner (1997) and Barber and Lyon (1997) when using long-window returns. Finally, the use of annual empirical reference distributions mitigates biases in t-statistics due to overlapping return periods.

Annual CO strategy returns are highly significant, with t-statistics above 8. Note that the long-short strategy associated with CO requires a single portfolio rebalance per year, mitigating concerns that return predictability is solely attributable to transaction costs.[15]

[15]Transaction costs are important consideration when assessing the profitability of analyst-based investment strategy. For example, Barber et al. (2001) document that abnormal returns associated with analyst recommendations fail to exceed the transaction costs required to implement the investment strategy.

Panel A also demonstrates that strategy returns continue to accumulate over the second year following the portfolio formation at a decreasing rate, which is consistent with prices continuing to drift in the direction of the earnings surprise following the annual announcement. The final column of Panel A in Table 4 contains the cumulative raw return from initiating and holding a single hedge position across CO quintiles throughout the two years following portfolio formation. The average cumulative hedge return is 9.5%. The persistence of predictable returns over the two years following portfolio formation suggests that the market is slow to fully unravel valuation errors associated with predictable forecast errors.

Panel B of Table 4 provides market-adjusted returns across quintiles of CO. The main findings of Panel A are unchanged when using market-adjusted returns in Panel B, where high CO quintile firms earn 5.3% higher returns than low CO quintile firms. The fact that the average returns of the highest CO quintile exceed the average returns of the lowest CO quintile sheds light on the weights that investors place on analyst and characteristic forecasts. Predictably positive differences in future returns across high and low CO portfolios indicates that market expectations of future earnings deviate from the optimal Bayesian weighting of the two forecasts. Specifically, positive CO strategy returns indicate that the market places larger than efficient weights on analyst forecasts and smaller than efficient weights on characteristic forecasts.

Table 5 examines the predictive power of characteristic forecast optimism for six- and twelve-month future returns in a multivariate setting. Panel A presents regression results where the dependent variable equals market-adjusted returns over the six months following the portfolio formation date. For ease of interpretation, all control variables are again sorted into quintiles ranging from 0 to 1. Columns (1) and (2) contain regression results after decoupling CO into scaled characteristic and analyst forecasts. Column (1) demonstrates that analyst forecasts do not by themselves have a significant predictive relation with future returns. Controlling for both components, column (2) shows that characteristic forecasts have a significant positive relation with future returns, whereas analyst forecasts have a significant negative relation. The fact that characteristic forecasts positively predict future returns only when controlling for analyst forecasts is consistent with investor expectations aligning with analyst forecasts and deviations between the two forecasts signaling erroneous performance expectations embedded in prices that are subsequently reversed. Not surprisingly, column (3) provides supporting evidence when using characteristic forecast optimism as the main predictive variable. I include controls for accruals, firm size, book-to-market, long-term growth, and momentum to demonstrate that the CO-return relation is distinct from other variables known to predict returns in cross-sectional tests. Because I calculate characteristic forecasts from past earnings, characteristic forecast optimism is intuitively linked to past analyst forecast errors. Thus, a significant concern is whether the CO-return relation emanates from the tendency of prices to drift in the direction of past earnings surprises, known as post-earnings announcement drift (PEAD). To mitigate this concern, I also control for PEAD, defined as the firm's most recent quarterly earnings minus the consensus forecast immediately prior to the announcement, and scaled by price.[16] Across columns (3) through (5), the coefficient on CO remains statistically significant for all specifications. Finally, as a proxy for private information embedded in analyst forecasts, I control for the value-to-price (VTP) ratio as calculated in Frankel and Lee (1998). VTP is the Edwards-Bell-Ohlson (EBO) fundamental value estimate derived from analyst forecasts, using a constant discount rate of 10% per year, and scaled by equity share price (see Appendix B for more details).

Column (6) of Panel A demonstrates that CO retains predictive power for returns incremental to VTP, where the VTP coefficient is positive but insignificant. Panel B of Table 5 contains regression results when the dependent variable is RET(1,12). These tests produce similar inferences to Panel A, except that VTP is significantly, positively predictive of returns. The difference in predictive power of VTP in Panels A and B is consistent with the findings in Frankel and Lee (1998) that the returns to VTP strategies increase in the

[16] I uses quarterly, rather than annual, announcement surprises to be consistent with the existing literature on post-earnings announcement drift (Bernard and Thomas (1990)). The results are qualitatively similar when controlling for standardized unexpected earnings (SUE) in place of PEAD.

duration of the holding period. The CO coefficient remains positive and significant across all specifications indicating that CO is a fairly robust and distinct predictor of future returns.

Figure 2 plots annual differences in raw returns for firms in the highest and lowest quintiles of characteristic forecast optimism. The plot demonstrates that the CO strategy produces positive returns in 22 out of 30 years during the 1980-2009 sample window. Moreover, the magnitude of the average return during negative years (-4.3%) is one-half of the magnitude of the average return during positive years (8.6%). Finally, the strategy performs well in periods of sharp economic downturn, providing an average return of 13.2% during years corresponding to the market crash of 1987, the Tech-Bubble collapse of 2001, and the global financial crises of 2009. To the extent that strategy returns reflect compensation for bearing systematic risk, one may have expected the opposite result, namely that returns are lowest during recessionary periods when investors' marginal utility for capital is highest.

4.4. Additional Return Tests

An alternative interpretation of the positive CO-return relation is that return predictability manifests in response to priced risk correlated with characteristic forecast optimism. To mitigate concerns that CO reflects firms' sensitivities to known risk proxies, Panel A of Table 6 contains portfolio alphas from orthogonalizing CO strategy returns to the Fama-French and momentum factors (Fama and French (1992), Fama and French (1993)):

$$R_{CO,m} = \alpha + \beta_1(R_{mkt,m} - R_{f,m}) + \beta_1 HML_m + \beta_2 SMB_m + \beta_3 UMD_m + \epsilon_{i,m} \tag{12}$$

where firms are assigned to quintiles once a year and held for periods of six and twelve months. $R_{CO,m}$ is the equal-weighted return from buying (selling) firms in the highest (lowest) quintile of CO in month m, $R_{mkt,t} - R_{f,t}$ equals the excess market return, HML_m equals the return on the high-minus-low book-to-market strategy, SMB_m equals the return on the small-minus-big strategy, and UMD_m equals the return on the up-minus-down momentum strategy.

The intercept from estimating equation (12) is significant and positive across both holding periods incremental to the factors, which mitigates risk-based explanations of the positive CO-return relation. The intercepts in columns (1) through (3), corresponding to six-month holding periods, range from 0.526 to 0.446 indicating that the strategy results in an average annualized alpha of approximately 5% during the sample window. The coefficient on $R_{mkt,m} - R_{f,m}$ is negative indicating that the CO strategy possesses a negative market beta. Similarly, the coefficient on SMB_m is negative, consistent with the portfolio strategy relying upon larger firms with analyst coverage.

A common approach to determining whether a given signal reflects biased earnings expectations is to infer expectation errors implied by the market's response to earnings news (e.g., La Porta et al. (1997)). Panel B of Table 6 contains regression results of quarterly earnings announcement returns subsequent to the portfolio formation date. I obtain quarterly earnings announcement dates from Compustat and calculate announcement window returns from t-1 to t+1, where t is the quarterly announcement date.

I find that CO positively incrementally predicts announcement-window returns during the first quarterly announcement. The coefficient on CO in column (1) is 0.338, indicating that high CO firms outperform low CO firms by an average of 33.8 basis points during the announcement. If the 5.3% market-adjusted strategy returns documented in Table 4 are evenly distributed across a year, one would expect that firms earn approximately 2.1 (5.3/252) basis points per day, and 6.3 basis points during the three-day announcement window, which is approximately one-fifth of the observed announcement return. Column (2) demonstrates that CO does not significantly predict announcement-window returns during the second quarterly announcement. Although the results in Panel B document some concentration of returns at earnings announcements, the relatively low concentration, combined with the finding that CO predicts revisions in analyst forecasts and recommendations, suggests that a substantial portion of expectation errors embedded in prices are gradually corrected during non-announcement periods.

4.5. Conditional Return Tests

The preceding sections establish a robust link between characteristic forecast optimism and future returns. In this section, I re-examine this link after conditioning on firm characteristics. The methodology in this paper relies on detecting erroneous earnings expectations embedded in equity prices. Thus, given that characteristic forecast optimism predicts analyst earnings forecast errors, I expect strategy returns to increase in firms' stock price sensitivities to earnings news. Following Abarbanell and Lehavy (2003), I measure stock price sensitivity using firms' consensus buy/sell recommendation as of the portfolio formation date. Abarbanell and Lehavy (2003) argue that buy/sell recommendations correspond to a latent variable measuring a collection of firm incentives to meet or beat analyst forecasts. I obtain consensus buy/sell recommendations from IBES, where ratings range from 1=strong buy to 5=strong sell. I divide the sample into three groups to reflect the level of the buy/sell recommendation. Firms with a mean buy/sell recommendation between 1 and 1.25 are coded as 'BUY', 1.25 and 2.5 as 'HOLD', and greater than 2.5 as 'SELL'. The asymmetric cutoff points reflects the fact that the distribution of buy/sell recommendations is heavily skewed toward buy-recommendations. Sorting firms into terciles of the concensus recommendation produces qualitatively similar results. Panel A of Table 7 presents the time-series average return for firms based on a two-way independent sort of CO and recommendation subsamples. CO strategy returns are most pronounced among firms with buy-recommendations, where the average annual return is 9.4% (t-statistic=7.681). Although CO quintiles predict statistically significant returns across each recommendation group, CO fails to predict economically significant returns in the SELL portfolio, consistent with buy/sell recommendations capturing an amplification factor linking earnings news and realized returns.

Panel B presents the time-series average return for firms based on a two-way independent sort of CO and SIZE. Strategy returns are most pronounced among small firms. One interpretation of this result is that the overweighting of analyst forecasts is most pronounced among firms in poor information environments. Intuitively, this suggests that high information gathering costs may lead investors to rely more heavily on analysts as information intermediaries. Panel C sorts firms based on CO and the book-to-market ratio. Note that while the strategy returns are statistically significant across all terciles of BTM, they are most pronounced for firms in the highest tercile, producing 7.7% per year. To the extent that BTM reflects investor neglect, the results suggest that investors overweight analyst forecasts to a greater degree among neglected firms with poor information environments.

Panel D demonstrates that the profitability of the CO strategy is most pronounced among the highest tercile of absolute accruals, ABAC, resulting in an average annual return of 9.6% per year. The use of absolute accruals is motivated by Hutton, Marcus, and Tehranian (2009) who find that absolute accruals measure earnings opacity, where higher values indicate more uncertainty regarding the mapping between current and future earnings. Thus, finding that the CO-return relation is increasing in absolute accruals is consistent with investors being more likely to overweight analyst forecasts when financial statements are less transparent. Panel E presents CO strategy returns across terciles of PEAD, the most recent analyst-based earnings surprise. The results demonstrate that strategy returns are largest following negative earnings surprises. Because negative earnings news is less persistent than positive earnings news (Hayn (1995)), these results provide additional supporting evidence that investors are more likely to overweight analyst forecasts when uncertain about the mapping between current and future earnings.

Table 8 examines the interaction effects documented in Table 7 within a multivariate regression. To mimic the construction of Table 7, LowSIZE is a dummy variable that equals one if the firm is in the lowest tercile of SIZE and HighABAC equals one for firms in the highest tercile of absolute accruals. The remaining interaction terms are defined analogously. Note that all of the interaction terms in columns (1) through (5), except for CO*lowMTB, are significant and positive. The interaction terms in column (6) demonstrate these same interaction effects remain significant in a multivariate setting, consistent with each conditioning variable capturing a distinct factor influencing the weights allocated to analyst forecasts.

Having established a significant relation between characteristic forecast optimism and future returns, I next examine variation in strategy returns over time. To the extent that investors predictably benchmark their earnings expectations to analyst forecasts, I expect that the CO-return relation is strongest in periods of high investor sentiment when analysts face the greatest incentives to bias their forecasts. Baker and Wurgler (2006) construct their sentiment index from several measures of equity market activity likely correlated with analysts' incentives to bias their forecasts: average first-day IPO returns, the number of IPOs, market-wide share turnover, and equity share issuances. Consistent with this idea, Groysberg, Healy, and Maber (2011) documents that variation in pay across analysts and the total pool of economy-wide analyst compensation increase during periods of high investor sentiment. Similarly, Hribar and McInnis (2011) and Walther and Willis (2011) provide evidence that analyst forecasts are least accurate during periods of high investor sentiment. This suggests that analyst employment incentives (Z_i in the terminology of Section 2) play a larger role in determining analyst forecasts when investor sentiment is high. Thus, if investors fail to fully undo the influence of temporal variation in analyst incentives on their forecasts, I expect that the CO-return relation is strongest when investor sentiment is high because larger analyst errors translate into larger reversals of investor expectation errors.

To examine this hypothesis, I use an annual sentiment measure from Baker and Wurgler (2006), orthogonalized to macroeconomic business cycle indicators. I divide the sample window into three groups based on the annual Baker and Wurgler investor sentiment index. Within each group, I calculate the average annual absolute analyst foreast error (|BIAS|) and CO-strategy return. Figure 3 demonstrates that average absolute analyst errors and CO-strategy returns are both monotonically increasing in investor sentiment. The CO strategy produces an average annual return of 1% during periods of low sentiment, whereas the same strategy produces average returns exceeding 10% in periods of high sentiment.

Figure 3 suggests that the pricing implications of investors overweighting analyst forecasts are closely tied to investor sentiment. To further investigate this relation, I calculate the extent to which investors overweight analyst forecasts using equation (A.9) in Appendix A. Specifically, I measure overweighting as the average annual difference in raw returns for firms in the highest and lowest CO quintiles, scaled by the pooled annual average of CO. The resulting measure is truncated at -1 and +1, where higher values indicate that investors place larger than efficient weights on analyst forecasts and vice versa.

Figure 4 presents year-by-year plots of the overweighting of analysts forecasts along side the Baker and Wurgler investor sentiment index. The figure demonstrates a strong positive correlation between the two time series. In untabulated results, I find that the annual Pearson correlation is 0.55. Together Figures 3 and 4 establish a strong positive relation between investor sentiment and overweighting, consistent with predictable biases in analyst forecasts resulting in larger distortions in prices during high investor sentiment regimes, corresponding to periods when analysts face heightened incentives to bias forecasts.

5. Robustness and Additional Analyses

5.1. Comparison to Traditional Approach

In this section, I compare the characteristic approach to traditional approaches relying on regression-based fittings of past forecast errors. To facilitate a direct comparison, I fit past forecast errors to the same firm characteristics used in equation (9) when constructing characteristic forecasts. Specifically, in year t, I estimate the following cross-sectional regression:

$$\begin{aligned} FE_{j,t} =& \beta_0 + \beta_1 E_{j,t-1} + \beta_2 NEGE_{j,t-1} + \beta_3 ACC^-_{j,t-1} + \beta_4 ACC^+_{j,t-1} + \beta_5 AG_{j,t-1} \\ &+ \beta_6 DD_{j,t-1} + \beta_7 DIV_{j,t-1} + \beta_8 B/M_{j,t-1} + \beta_9 Price_{j,t-1} + \epsilon_{j,t-1} \end{aligned} \tag{13}$$

where FE is measured five months following firms' fiscal year end, defined as actual earnings minus the prevailing consensus earnings estimate, scaled by total assets per share.

Mirroring the construction of characteristic earnings forecasts, I historically estimate equation (13) and apply the resulting coefficients to firm characteristics in year t to obtain a predicted forecast error for year t+1 earnings:

$$PFE_{j,t} \equiv \hat{\beta}_0 + \hat{\beta}_1 E_{j,t} + \hat{\beta}_2 NEGE_{j,t} + \hat{\beta}_3 ACC^{-}_{j,t} + \hat{\beta}_4 ACC^{+}_{j,t} + \hat{\beta}_5 AG_{j,t} + \hat{\beta}_6 DD_{j,t} + \hat{\beta}_7 DIV_{j,t} + \hat{\beta}_8 B/M_{j,t} + \hat{\beta}_9 Price_{j,t} \tag{14}$$

where the resulting fitted value reflects the predicted forecast error. PFE and CO have a Pearson (Spearman) correlation of 0.33 (0.27), indicating a strong correlation between the two measures (correlations untabulated). In Table 9, I test the relative predictive power of CO and PFE for future forecast errors, revisions, and returns. CO and PFE are both assigned to quintiles, ranging from 0 to 1, to facilitate a comparison of regression coefficients.

Column (1) demonstrates that PFE positively predicts analyst forecast errors, incremental to standard controls. Column (2) demonstrates that both CO and PFE possess predictive power for BIAS. However, the t-statistic corresponding to CO is roughly three times as large as the t-statistic corresponding to PFE, suggesting that CO possesses significantly higher predictive power. Similarly, in untabulated results, an F-test of equal coefficients across CO and PFE is clearly rejected, with a corresponding F-statistic of 44.01.

Columns (3) and (4) compare the predictive power of CO and PFE for revisions in analyst earnings forecasts, REV. Column (3) demonstrates that PFE contains some predictive power for forecast revisions (t-statistic=1.92) and column (4) demonstrates that CO contains significant predictive power for forecast revisions relative to PFE. More importantly, PFE is not significantly related to REV after controlling for CO. Finally, columns (5) and (6) demonstrate that CO is significantly related to future returns whereas PFE is not.

Given that the traditional approach outlined by equations (13) and (14) relies on fitting forecast errors to the firm characteristics selected by Fama and French (2000) to forecast profitability, it is reasonable to question whether the tests in Table 9 reflect a 'fair fight'. In other words, does the characteristic approach outperform the traditional approach simply because the fitting variables are selected to forecast earnings rather than analyst errors? To address this question, I compare the predictive power of characteristic forecast optimism relative to two existing forecast error prediction models designed by Hughes, Liu, and Su (2008) and Frankel and Lee (1998). The Hughes, Liu, and Su (2008) model consists of fitting forecast errors to the following eight variables:

- ACC: accruals scaled by total assets
- LTG: mean consensus long-term growth forecast
- Sales Growth: five-year percentage growth in sales
- ΔPPE: annual change of property plant and equipment
- ΔOLA: annual change of other long-term assets
- PEAD: the most recent analyst-based quarterly earnings surprise
- RET: market-adjusted stock returns over the past 12 months
- REV_{HIST}: historical revisions of analysts' two-year forecasts in the past three months

Similarly, following Frankel and Lee (1998), the second model consists of fitting forecast errors the following four variables:

- Book-to-price: book equity per share scaled by price
- Sales Growth: five-year percentage growth in sales
- LTG: mean consensus long-term growth forecast
- OP: $(V_f\text{-}V_W)/|V_W|$ where V_f (V_W) is an Edwards-Bell-Ohlson fundamental value estimate derived from analyst (characteristic) forecasts, using a constant discount rate of 10% per year. See Appendix B for more details.

I re-estimate equations (13) and (14) using both sets of variables listed above. Whereas Frankel and Lee (1998) fit forecast errors to percentile ranks of the above variables, Hughes, Liu, and Su (2008) use continuous (i.e. unranked) variables. For parsimony, I use an intermediate approach that ranks the above forecasting variables into deciles, although the results appear insensitive to this choice.

Panels A and B of Table 10 contain results from regressing BIAS, REV, and RET(1,12) on predicted forecast errors, denoted by $\widehat{FE}^T$, estimated using the traditional approach in Hughes, Liu, and Su (2008) and Frankel and Lee (1998), respectively. In both Panels A and B, column (1) demonstrates that $\widehat{FE}^T$ predicts analyst forecast errors incremental to SIZE, BTM, and MOMEN. Note, however, that $\widehat{FE}^T$ is no longer significant after controlling for the control variables used in Table 5: ACC, LTG, and PEAD. The failure of $\widehat{FE}^T$ to predict forecast errors after controlling for these characteristics indicates that predicted forecast errors calculated under the traditional approach do not contribute to the prediction of forecast errors incremental to contemporaneously observable standard control variables. Columns (4) through (6) of Panels A and B show a similar pattern when REV is the dependent variable. The final three columns of both panels contain results from regressing future returns on predicted forecast errors. Consistent with the findings in Hughes, Liu, and Su (2008), $\widehat{FE}^T$ is not a robust predictor of future returns in cross-sectional tests. These results again favor the use of the characteristic approach and are consistent with the methodological concerns associated with the traditional approach as outlined in Section 2.

5.2. Additional Analyses

Three additional robustness checks related to the estimation of characteristic forecasts merit mentioning. First, the use of price and book-to-market in creating characteristic forecasts raises concerns that characteristic forecast optimism predicts future returns through its dependence on share prices. To mitigate these concerns, I remove both variables from the forecasting equations (i.e., equations (9) and (10)) and find qualitatively similar results. This is not surprising given that book-to-market fails to offer predictive power for one-year ahead earnings. Similarly, price is positively predictive of future earnings, indicating a positive relation between CO and price, where the returns to value strategies tend to rely on purchasing lower price firms in terms of earnings-to-price or book-to-market. Second, additional tests reveal that a naive approach using only lagged earnings as the characteristic earnings forecast also predicts analyst forecast errors and future returns, though the predictive power attenuates relative to the full characteristic model. Finally, I find that including analyst forecasts in equations (9) and (10) yields characteristic forecasts which are biased estimates of realized earnings but does not eliminate the ability of CO to predict future returns.

5.3. Discussion

The evidence that I provide regarding the overweighting of analyst forecasts raises an obvious question: how could characteristic forecast optimism consistently predict future returns? There are several non-mutually exclusive explanations for this pattern. First, because I do not examine transaction costs, it is not clear that the pattern of return predictability represents available economic profit opportunities as defined by Jensen (1978). However, because the investment strategy requires a single portfolio rebalance for each firm-year, it seems unlikely that transaction costs would fully account for this pattern.

Similar to the arguments in Lakonishok, Shleifer, and Vishny (1994), a second potential explanation is that investors simply did not know about the efficacy of the cross-sectional regression approach to forecasting earnings and the characteristic approach to predicting analyst errors. Until recently, time-series forecasts of earnings were the predominant approach used within the academic literature. In contrast to the characteristic approach, prior research demonstrates that time-series forecasts are significantly less accurate than analyst forecasts (Brown and Rozeff (1978), Brown et al. (1987), O'Brien (1988)), casting doubt on their ability to discriminate between overly optimistic and pessimistic analyst forecasts.

A related explanation pertains to the incentives of institutional money managers. Managers may face incentives to take positions that are justifable *ex post*. Trading in line with concensus analyst forecasts may appear more prudent than trading against their recommendations and thus shield managers from legal culpability that arises from subsequent investment losses. Similarly, because the strategy employed in this paper relies on FY1 forecast errors, investors' investment horizons may be too short to capture abnormal returns associated with characteristic forecast optimism (Lakonishok, Shleifer, and Vishny (1994)).

A final potential explanation relates to behavioral tendencies documented in the pyschology literature. Analyst forecasts are a salient component of modern capital markets and are widely available in various forms including online, in media interviews, and in news articles. The ease with which investors access analyst forecasts may contribute to overweighting because of minimal computational costs for use within valuation models. Supporting this interpretation, Kahneman (1973) and Griffin and Tversky (1992) provide evidence that individuals weight available signals by their salience and pay insufficient regard to the signal's credibility. In providing evidence that investors overweight analyst forecasts, this paper aligns with a growing literature on the role of limited investor attention and cognitive resources in determining asset prices (e.g., DellaVigna and Pollet (2007), Hirshleifer, Lim, and Teoh (2009), Wahlen and Wieland (2010), and Da and Warachka (2011)). Together, the findings of this paper suggests that prices do not reflect the predictable component of analyst errors in a timely fashion but does not distinguish between these competing explanations.

6. Conclusion

This paper provides evidence that investors systematically overweight analyst forecasts by demonstrating that prices do not fully reflect the predictable component of analyst forecast errors in a timely fashion. The central implication of these findings is that investors fail to fully undo predictable biases in analyst forecasts and, as a result, distortions in analyst forecasts can influence the information content of prices.

Evidence that investors overweight analyst forecasts conflicts with conclusions in prior research relying on traditional approaches to predicting analyst forecast errors. Traditional approaches are subject to correlated omitted variable bias whenever the variables used to predict forecast errors are correlated with unobservable inputs to analyst forecasts. I develop and implement a new approach that mitigates this bias by contrasting 'characteristic forecasts' of earnings with those issued by analysts. I estimate characteristic forecasts using large sample relations to map current firm characteristics into forecasts of future earnings and demonstrate that evaluating analyst forecasts relative to characteristic forecasts offers significant predictive power for analyst errors and future returns.

I find that firms with characteristic forecasts exceeding the consensus analyst forecast tend to have realized earnings that exceed the consensus, and vice versa. Similarly, analysts subsequently revise their earnings forecasts and buy/sell recommendations in the direction of characteristic forecasts leading up to earnings announcements. This evidence suggest that analysts are slow to incorporate the information embedded in characteristic forecasts and that overreliance on analyst forecasts will likely result in valuation errors.

I find that stock prices behave as if investors overweight analyst forecasts and underweight characteristic forecasts relative to the optimal Bayesian weights. Specifically, I document consistent abnormal returns to a strategy that buys firms with characteristic forecasts above analyst forecasts and sells firms with characteristic forecasts below analyst forecasts. Strategy returns significantly increase through contextual analysis and display a number of intuitive relations with firm characteristics and market trends. For example, returns are increasing in the sensitivity of firms' stock price to earnings news and the uncertainty between current and future earnings and are most pronounced during periods of high investor sentiment. The magnitude and consistency of return prediction is striking in light of prior research concluding that investors efficiently weight analyst forecasts.

Taken together, the findings of this paper have implications for practitioners, regulators, and researchers. First for practitioners, the findings support using characteristic forecasts as a means of evaluating analysts and identifying potential mispricing. Similarly, characteristic and analyst forecasts offer incremental predictive power for future earnings, which supports the use of both forecasts when valuing firms. Second, the evidence that investors systematically overweight analyst forecasts suggests that market regulators motivated by the efficient allocation of capital should pursue measures to improve analyst forecasts, such as the development of additional mechanisms reducing incentive misalignment between analysts and investors. Finally, for researchers, I propose a simple test of the efficient weighting of multiple earnings forecasts by relating forecast differences with future returns. Understanding how investors weight these forecasts can yield superior measures of the market's expectations of earnings and thus potentially improve estimates of earnings surprises and implied cost of capital that require these expectations as inputs.

Appendix A: Forecast Weighting and Future Returns

The following framework is adapted from the model of Chen and Jiang (2006) who provide evidence that analysts overweight private signals relative to public signals when issuing earnings forecasts. Unlike Chen and Jiang (2006) who model how analysts weight information, I examine the role of earnings forecasts in the development of market prices. Building upon the Chen and Jiang framework, I also examine how investors weight earnings signals and the implications of these weights for future returns.

In this framework, I assume a two-period setting in which investors form earnings expectations at period t and the realization of earnings is disclosed publicly at period t+1. Let E_j denote the realization of firm j's earnings. Assume that E_j is normally distributed with a zero mean and a non-zero variance.

Investors are initially unable to observe E_j in period t, but have access to two noisy signals regarding the realization of E_j. The first signal is the consensus analyst forecast. Let AF_j denote the consensus forecast of earnings, where AF_j can be expressed as:

$$AF_j = E_j + \epsilon_j^{AF} \tag{A.1}$$

where $\epsilon_j^{AF} \sim N(\mu^{AF}, \frac{1}{\rho^{AF}})$ is the firm-specific consensus forecast error, μ^{AF} reflects the average consensus error, and $\frac{1}{\rho^{AF}}$ denotes the variance of the analyst forecast error. Assume that although investors are unable to observe the realized forecast error, ϵ_j^{AF}, in period t, investors know the distribution of ϵ_j^{AF} including the mean, μ^{AF}. Note that assuming $\mu^{AF} \neq 0$ is equivalent to assuming that analysts are biased on average.

The second observable signal in period t regarding future earnings is a forecast derived from a firm's publicly issued financial statements. Let CF_j denote the characteristic forecast, which can be expressed as:

$$CF_j = E_j + \epsilon_j^{CF} \tag{A.2}$$

where $\epsilon_j^{CF} \sim N(\mu^{CF}, \frac{1}{\rho^{CF}})$. The characteristic forecast error, ϵ_j^{CF}, is assumed to be independent of E_j and ϵ_j^{AF}. The assumption that ϵ_j^{CF} and ϵ_j^{AF} are uncorrelated adds to the tractability of the model but is not crucial for the analysis so long as they are not perfectly correlated (Chen and Jiang (2006)).

After observing CF_j and AF_j, investors face a decision problem in allocating weights across the two signals. Under Bayesian expectations, the period t optimal statistical forecast of earnings is a convex combination of the de-meaned warranted and analyst forecasts:

$$OP_j \equiv \mathbf{E}_t[E_j|I_t] = \theta(CF_j - \mu^{CF}) + (1-\theta)(AF_j - \mu^{AF}) \tag{A.3}$$

where $\mathbf{E}_t[\cdot]$ reflects the expectations operator with respect to period t given the market's information set, I_t, and $\theta \equiv \frac{\rho_{CF}}{\rho_{CF}+\rho_{AF}} \in [0,1]$ is the optimal weight placed on CF_j when forming expectations of the realized earnings.

Equation (A.3) captures an intuitive relation between the optimal weights and the relative noise of warranted and analyst forecasts. Specifically, the optimal weight placed on characteristic forecasts is increasing in the precision of the de-meaned characteristic forecast relative to the precision of the de-meaned analyst forecast, and vice-versa. As ρ^{CF} approaches zero, the variance of the characteristic forecast error approaches infinity and the optimal Bayesian forecast of earnings places zero weight on characteristic forecasts. Similarly, as ρ^{AF} increases relative to ρ^{CF}, the optimal forecast places a weight of one on characteristic forecasts.

Because CF_j and the distribution of ϵ_j^{CF} are publicly observable, an additional assumption is necessary to prevent analysts from incorporating the information content of the characteristic forecast into their forecast of earnings. I assume the existence of additional institutional incentives, such as the desire to generate trading volume, garner favorable treatment and information access from management, and secure lucrative investment banking deals, prevent analysts from issuing the optimal forecast, OP_j.

Investors are not assumed to necessarily apply the efficient weights to warranted and analyst forecasts when forming earnings expectations. Instead, the market is assumed to assign a weight δ to characteristic forecasts, where δ may not equal θ. The resulting market expectation of firm j's earnings MK_j is thus given as

$$MK_j \equiv \delta(CF_j - \mu^{CF}) + (1-\delta)(AF_j - \mu^{AF}) \tag{A.4}$$

Note that the optimal forecast, OP_j, equals the market forecast, MK_j, when $\delta = \theta$. The market is said to have misweighted the signals whenever $\delta \neq \theta$. More precisely, investor overweighting, underweighting, and misweighting are defined as follows:

> **Definition:** Assume that the market assigns weight δ to characteristic forecasts and weight $1-\delta$ to analyst forecasts, where the optimal weighting is given by θ in equation (A.3). Investors misweight signals when $\delta \neq \theta$. Moreover, the market is said to overweight (underweight) analyst forecasts when $\delta < \theta$ ($\theta < \delta$).

In this two-period framework, I assume that investors receive a liquidating dividend at period t+1, equal to the firm's realized earnings. Hence, the period t price for firm j, $p_{j,t}$, equals the market expectations of earnings:

$$p_{j,t} = MK_j \tag{A.5}$$

In period $t+1$, earnings are announced and prices adjust to reflect the realization of earnings:

$$p_{j,t+1} - p_{j,t} \equiv r_j = E_j - MK_j \tag{A.6}$$

where r_j is defined as the return from holding a share in firm j from period t to $t+1$.[17] A necessary condition for the efficient weighting of the signals is characterized via the null hypothesis that price changes in period t are not predictable given AF_j and CF_j. Market efficiency requires that investors are unable to obtain a positive expected profit by allocating weights to AF_j and CF_j that differ from the weights assigned by the market. Within this two-period framework, market efficiency can be characterized as follows:

$$\mathbf{E}_t[r_j|I_t] = \mathbf{E}_t[E_j - MK_j] = 0 \tag{A.7}$$

[17] An equivalent assumption is that prices equal a positive multiple of expected earnings. Hence, realized price changes are linearly related to changes in earnings expectations. For example, Liu et al. (2002) and Hughes et al (2008) model price changes as: $p_{j,t+1} - p_{j,t} = \phi(E_j - MK_j)$, where ϕ is a positive constant.

Substituting equations (A.3) and (A.4) into (A.7), expected returns can be expressed as

$$\mathbf{E}_t[r_j|I_t] = (\theta - \delta) \cdot (CF_j - \mu^{CF} - AF_j + \mu^{AF}) \tag{A.8}$$

Equation (A.8) implies that expected returns are unrelated to the difference between demeaned analyst and characteristic forecasts when investors efficiently weight the two signals (i.e. $\theta = \delta$).

An empirical implication of the above framework is that tests of optimal market weighting can be achieved by examining the realized returns of portfolios formed on the basis of forecast differences. Let $j \in H$ and $j \in L$ correspond to two distinct sets of N firms for which characteristic forecast optimism, $CO_j = CF_j - AF_j$, is highest and lowest, respectively, where $CF_j > AF_j$ for $j \in H$ and $CF_j < AF_j$ for $j \in L$. Similarly, denote the equal-weighted average expected return of firms $j \in K$ as $\bar{r}_K \equiv N^{-1} \sum_{j \in K}^{N} \mathbf{E}_t[r_j]$.

Then, using equation (A.6), the difference in expected returns across the high and low portfolios can be expressed as:

$$\bar{r}_H - \bar{r}_L = (\theta - \delta) \cdot \left[\frac{1}{N} \sum_{j \in H}^{N} (CF_j - AF_j) - \frac{1}{N} \sum_{j \in L}^{N} (CF_j - AF_j) \right] \tag{A.9}$$

Note that the portfolio-based approach characterized by equation (A.9) allows the researcher to look for evidence of overweighting without having to first estimate the average errors of the warranted and analyst forecasts, μ^{AF} and μ^{CF}. Equation (A.9) expresses differences between the expected returns of the high and low portfolios as the difference between the averages of CO_j multiplied by the difference between the efficient weights and those chosen by the market, $(\theta - \delta)$. Note that the term inside the brackets within equation (A.9) is positive by construction. Hence, equation (A.9) demonstrates that differences in CO_j across portfolios H and L are positively associated with expected returns when the market overweights analyst forecasts (i.e. $\theta > \delta$) and negatively associated with expected returns when the market underweights analyst forecasts (i.e. $\delta > \theta$). Similarly, the magnitude of the forecast difference has no relation with returns when the market weights analyst forecasts according to the efficient weights (i.e. $\theta = \delta$).

I test the hypothesis that investors overweight analyst forecasts by empirically implementing equation (A.9). I test whether sorting firms on the basis of characteristic forecast optimism also sorts firms in terms of future stock returns. Specifically, I hypothesize that firms for which CO_j is high (i.e. $j \in H$) have predictably and significantly higher average returns than firms for which CO_j is low (i.e. $j \in L$). From equation (A.9), significantly higher average returns for portfolio H than portfolio L is consistent with investors placing larger than efficient weights on analyst forecasts (i.e. $\delta > \theta$). Conversely, a statistically insignificant difference in returns across portfolios H and L is consistent with the investors choosing optimal weights.

Appendix B: Estimation of Fundamental Value

This appendix provides an overview of the calculation of the fundamental value estimates used throughout the text. I estimate firms' fundamental value using a discounted residual income model, commonly described as the Edwards-Bell-Ohlson valuation model. Following Gebhardt, Lee, and Swaminathan (2001), I assume clean surplus accounting such that fundamental value can be written as the sum of reported book value and the infinite sum of discounted residual income. Specifically, I estimate firms' fundamental value at time t as:

$$\begin{aligned} V_t = B_t + \frac{FROE_{t+1} - r_e}{(1+r_e)} B_t + \frac{FROE_{t+2} - r_e}{(1+r_e)^2} B_{t+1} + \sum_{i=3}^{T-1} \frac{FROE_{t+i} - r_e}{(1+r_e)^i} B_{t+i} \\ + \frac{FROE_{t+T} - r_e}{r_e(1+r_e)^{T-1}} B_{t+T+1} \end{aligned} \tag{B.1}$$

where I assume that T=12 as in Gebhardt, Lee, and Swaminathan (2001) and

- B_t is the book value per share from the most recent annual financial statement.
- B_{t+i} is forecasted book value per share for year $t+i$ using the clean surplus relation and assuming firms maintain their current dividend payout ratio.
- $FROE_{t+i}$ is the forecasted ROE for year $t+i$. For analyst forecasts of $t+1$ and $t+2$ earnings, I use the mean consensus analyst EPS forecast. For $t+3$, I multiply the consensus long-term growth forecast by the FY2 forecast. For warranted forecasts, I calculate one-, two-, and three-year ahead forecasts using equations (9) and (10) of the main text. Beyond year t+3, I forecast ROE using a linear interpolation of $FROE_{t+3}$ to the historical median for firms' Fama-French industry classification.
- r_e is firms' cost of equity capital, assumed to be a fixed constant of 10%.

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Figure 1: Sample Size by Year

Figure 1 plots the total number of firms and median characteristic and analyst EPS forecasts for each calendar year in the sample window. Analyst forecasts (shown in the dashed black line) are obtained from IBES as the most recent mean consensus forecasts made available immediately prior to the portfolio formation date five months following the firm's fiscal year end. Characteristic forecasts (shown in the solid black line) are obtained on yearly basis where historically-fitted coefficients are estimated from an earnings regression using data from the prior calendar year and applied to firms' most recent characteristics. The final sample used in this analysis consists of 51,591 firm-years spanning 1980-2009.

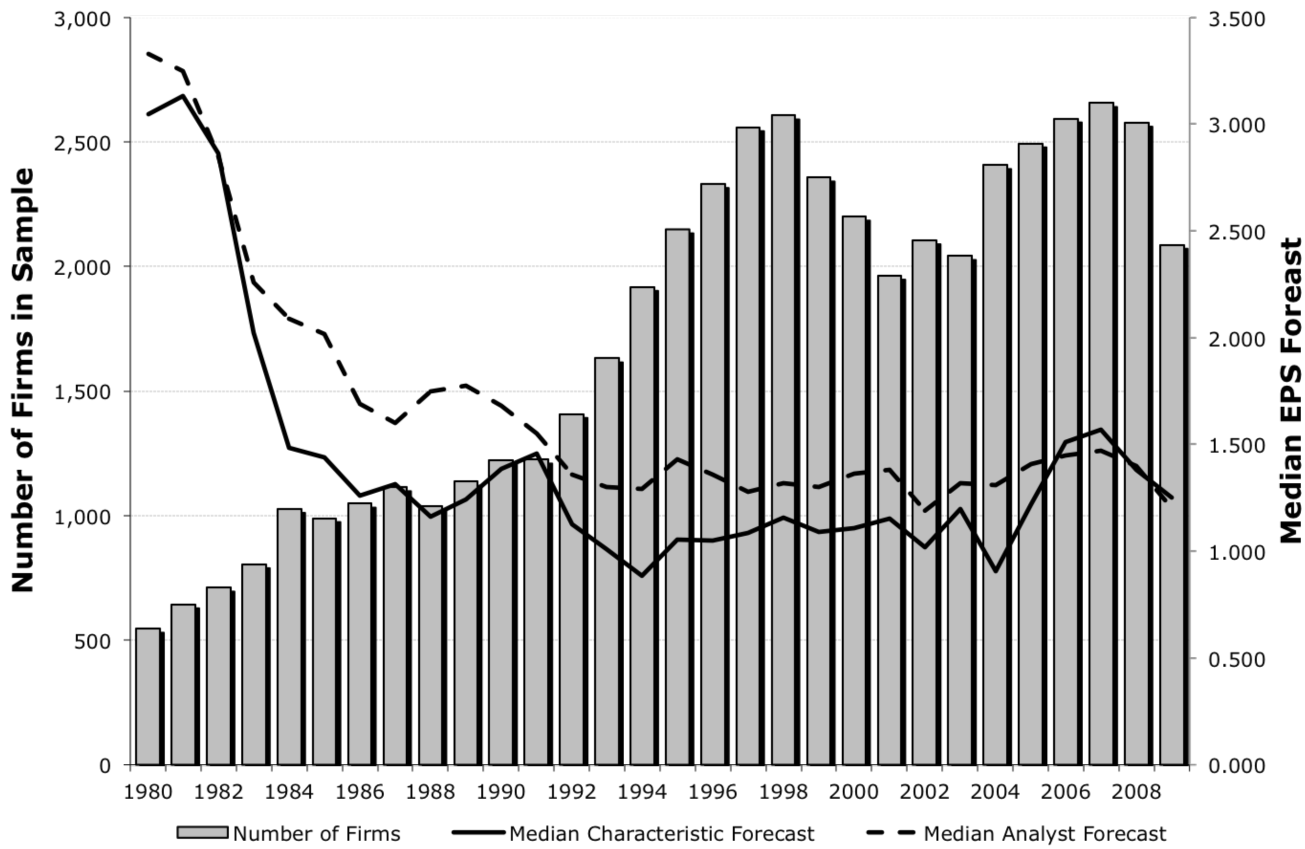

Figure 2: Long-Short Strategy Returns by Year

Figure 2 plots the annual difference in raw returns for firms in the highest and lowest quintiles of characteristic forecast optimism (CO). CO is defined as the difference in characteristic and analyst forecasts of annual earnings scaled by the firm's total assets. Analyst forecasts are obtained from IBES as the most recent mean consensus forecasts made available immediately prior to the portfolio formation date five months following the firm's fiscal year end. Characteristic forecasts are obtained on yearly basis where historically-fitted coefficients are estimated from an earnings regression using data from the prior calendar year and applied to firms' most recent characteristics. Raw returns are accumulated from the beginning of July and held through June of the following year. The sample used in this analysis consists of 51,591 firm-years spanning 1980-2009.

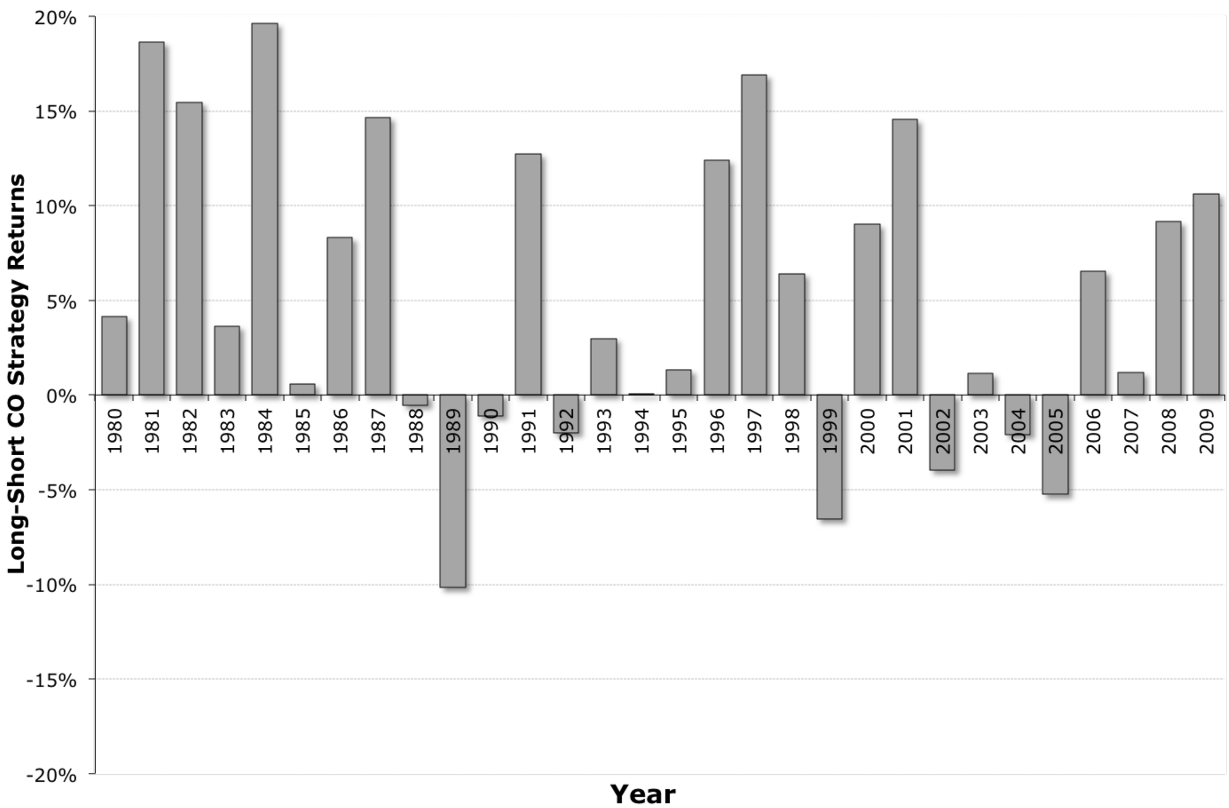

Figure 3: Absolute BIAS and Strategy Returns Across Sentiment Terciles

Figure 3 plots the average annual absolute analyst foreast error, |BIAS|, and return from a long (short) position in firms within the highest (lowest) quintile of characteristic forecast optimism (CO) across sentiment index terciles. CO is defined as the difference in firms' characteristic and analyst forecasts of annual earnings scaled by total assets per share. Analyst forecasts are obtained from IBES as the most recent mean consensus forecasts made available immediately prior to the portfolio formation date five months following the firm's fiscal year end. Characteristic forecasts are obtained on yearly basis where historically-fitted coefficients are estimated from an earnings regression using data from the prior calendar year and applied to firms' most recent characteristics. |BIAS| is defined as absolute value of the realized difference between earnings as reported in Compustat and the prevailing consensus forecast, scaled by total assets per share. The investor sentiment index corresponds to the measure used in Baker and Wurgler (2006), orthogonalized to macroeconomic indicators.

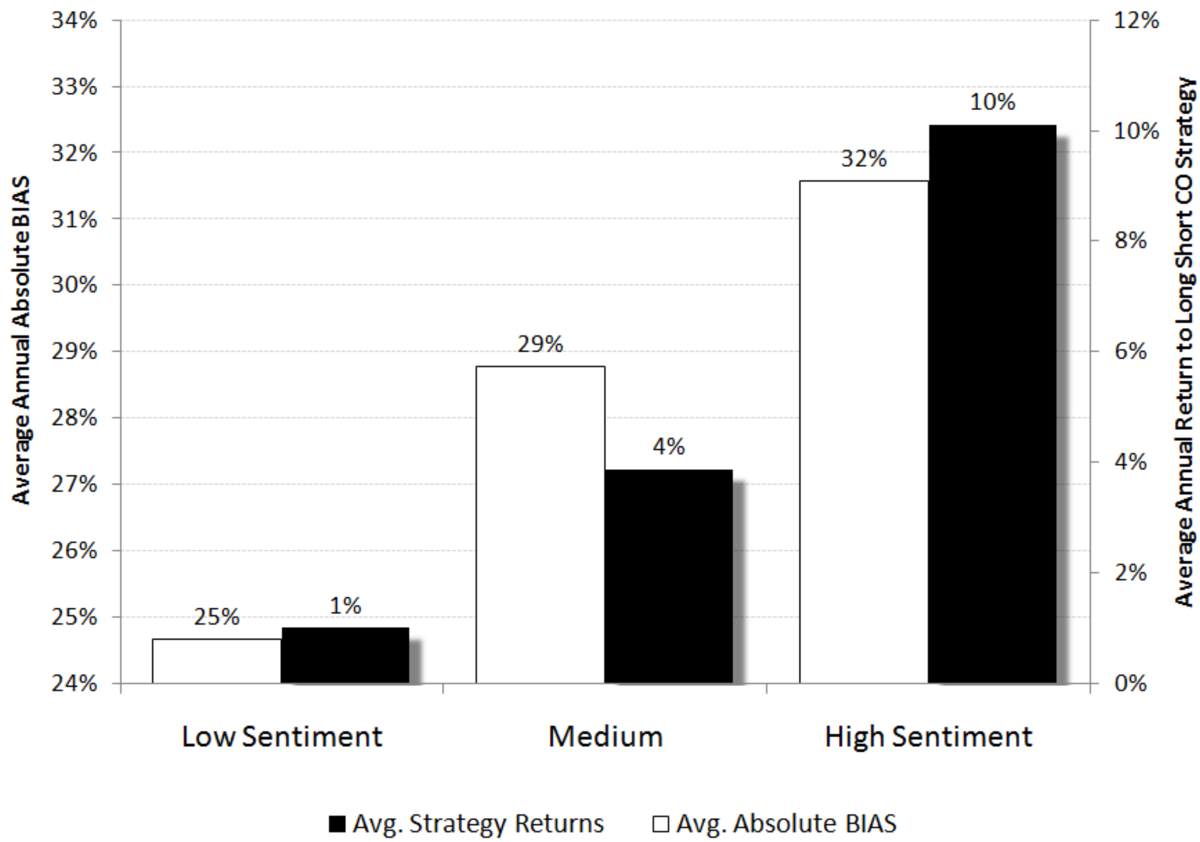

Figure 4: Relative Forecast Weights and Investor Sentiment Index

Figure 4 plots annual relative forecast weights and investor sentiment index values. Relative forecasts weights are defined in Appendix A and calculated as the average annual difference in raw returns for firms in the highest and lowest quintiles of characteristic forecast optimism (CO), scaled by the pooled annual average of CO. CO is defined as the difference in characteristic and analyst forecasts of annual earnings scaled by the firm's total assets. Analyst forecasts are obtained from IBES as the most recent mean consensus forecasts made available immediately prior to the portfolio formation date five months following the firm's fiscal year end. Characteristic forecasts are obtained on yearly basis where historically-fitted coefficients are estimated from an earnings regression using data from the prior calendar year and applied to the firm's most recent annual financial statements. The investor sentiment index corresponds to the measure used in Baker and Wurgler (2006), orthogonalized to macroeconomic indicators.

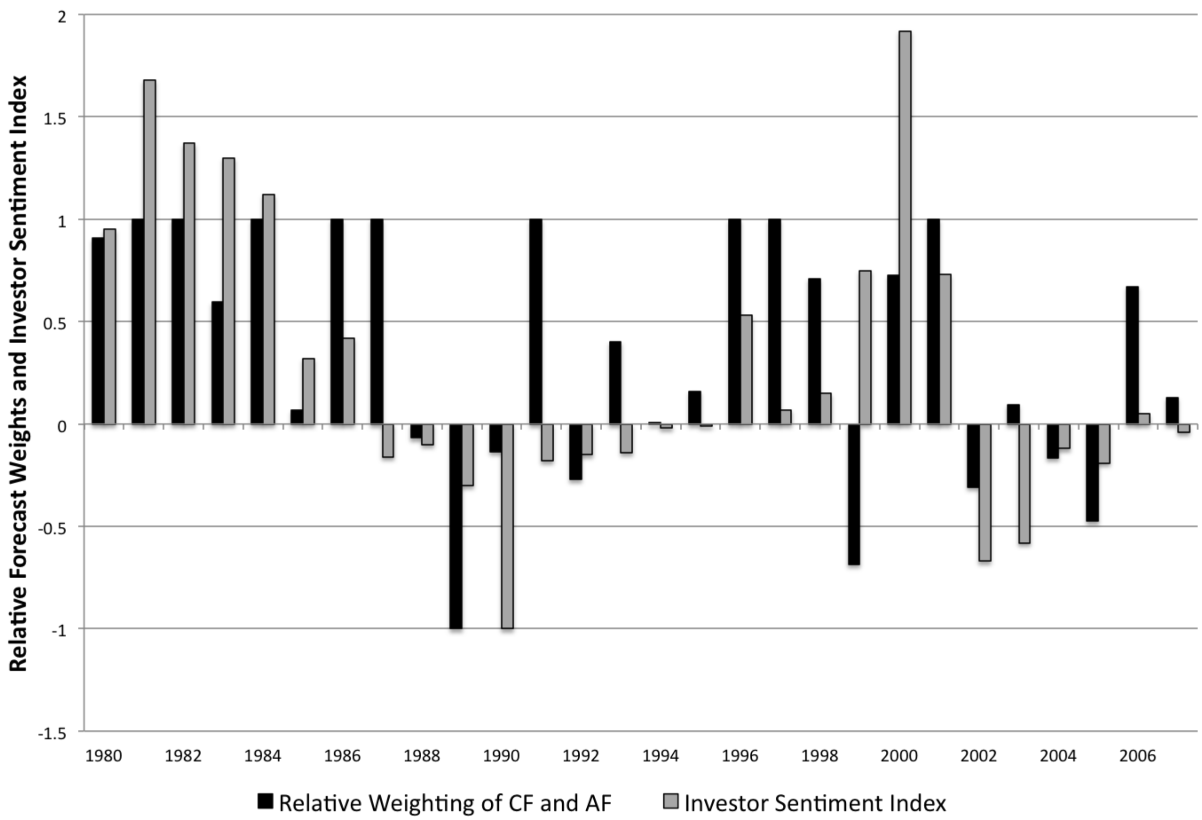

Table 1: Earnings Forecasts

Panel A presents the average regression coefficients from annual cross-sectional regressions of earnings before extraordinary items adjusted for special items. In each year of the sample, earnings are regressed on lagged book-to-market (B/M), share price (Price), a dummy variable indicating negative earnings (NEGE), earnings before extraordinary items adjusted for special items (E), negative accruals per share (-ACC), positive accruals per share (+ACC), asset growth as a percentage of lagged assets (AG), a dummy variable identifying non-dividend paying firms (DD), and dividends per share (DIV). The regression is fitted each year using data from the prior year. Mean coefficients are shown above t-statistics in parentheses. Analyst forecasts (AF) are obtained from IBES as the most recent mean consensus forecasts made available immediately prior to the portfolio formation date five months after the firm's fiscal year end. Characteristic forecasts (CF) are obtained on yearly basis where historically-fitted coefficients are estimated from an earnings regression using data from the prior calendar year and applied to firms' most recent characteristics. Panel B presents the time-series mean of yearly average forecast errors per share, defined as realized earnings (RE) minus the corresponding forecast, both on a per share basis. t-statistics are based on the 30-year time-series average forecast error over the 1980-2009 sample window. Panel B also contains Pearson correlations of characteristic forecasts, analyst consensus forecasts, and realized earnings (RE). Panel C contains the results from regressing realized earnings on CF and AF, where t-statistics are shown in parentheses and are based on two-way clustered standard errors by year and industry. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level. The sample used in this analysis consists of 51,591 firm-years spanning 1980-2009.

Panel A: Earnings Regressions

	Avg. Coefficient	Avg. t-statistic
Intercept	0.232	3.053
E	0.672	27.469
NEGE	-0.631	-9.279
-ACC	0.014	0.754
+ACC	-0.028	-1.931
AG	-0.093	-3.060
DD	-0.065	-1.335
B/M	-0.053	-0.197
Price	0.010	4.767
DIV	0.130	3.092
Avg. Adj. R^2 (%)	56.1	

Panel B: Average Forecast Errors and Correlations

	corr(Forecast, RE)	corr(CF, AF)	Mean Error	t-statistic
CF	0.729	0.851	0.112	1.587
AF	0.778	0.851	-0.216	-4.846

Panel C: Regression of Realized Earnings

	(1)	(2)	(3)
Intercept	0.110**	-0.277***	-0.291***
	(2.20)	(-11.49)	(-11.71)
CF	1.001***	–	0.242***
	(19.78)	–	(2.81)
AF	–	1.054***	0.857***
	–	(42.27)	(13.87)
Adj. R^2 (%)	47.8	58.0	58.8

P-Value for Test of Coefficient on CF=1: 0.8620
P-Value for Test of Coefficient on AF=1: 0.000
P-Value for Test of Equal Coefficients CF=AF: 0.000

Table 2: Descriptive Statistics by Quintiles of CO

Panels A presents mean descriptive statistics by quintiles of CO. CO is defined as the difference in characteristic forecasts (CF) and analyst forecasts (AF) of annual earnings scaled by the firm's total assets per share. Analyst forecasts are obtained from IBES as the most recent mean consensus forecasts made available immediately prior to the portfolio formation date five months following the firm's fiscal year end. Characteristic forecasts are obtained on yearly basis where historically-fitted coefficients are estimated from an earnings regression using data from the prior calendar year and applied to firms' most recent characteristics. SIZE is defined as the log of market capitalization and LBM is defined as the log of book-to-market ratio. P-values for the null hypothesis of no difference across the high and low CO quintiles is based on the 30-year time-series average difference across the extreme quintiles of CO over the 1980-2009 sample window. Panel B contains descriptive statistics of analyst forecast errors. BIAS is defined as realized difference between earnings as reported in Compustat and the prevailing consensus forecast, scaled by total assets per share. I calculate the median value of BIAS each year and report the median and mean of the annual time-series. The table also contains the percentage of firm-years for which (i) realized earnings are less than the analyst forecast and (ii) realized earnings are greater than the analyst forecast. The sample used in this analysis consists of 51,591 firm-years spanning 1980-2009.

Panel A: Mean Summary Statistics by Quintiles of CO

	CF	AF	SIZE	LBM
1 (Low CO)	0.942	1.747	12.860	0.320
2	1.586	2.173	13.271	0.389
3	1.866	2.331	13.382	0.453
4	2.012	2.265	13.279	0.506
5 (High CO)	1.966	1.552	12.991	0.503
High-Low	1.024	-0.196	0.131	0.183
P-Value for H_0: High-Low=0	0.000	0.126	0.190	0.000

Panel B: Descriptive Statistics of Analyst Errors by Quintiles of CO

	Median BIAS	Mean BIAS	Earnings<AF	Earnings>AF
1 (Low CO)	-2.851	-6.269	0.602	0.398
2	-0.482	-1.626	0.560	0.440
3	-0.175	-0.745	0.550	0.450
4	-0.006	-0.321	0.520	0.480
5 (High CO)	0.006	-0.482	0.499	0.501
High-Low	2.857	5.787	-0.103	0.103
P-Value for H_0: High-Low=0	0.000	0.000	–	–

Table 3: Predicting Forecast Errors and Revisions

Panels A presents results from regressing realized forecast errors on quintiles of CO and additional controls. In Panel A, BIAS (IBIAS) is defined as realized difference between earnings as reported in Compustat (IBES) and the prevailing consensus forecast, scaled by total assets per share. CO equals the difference in characteristic forecasts (CF) and analyst forecasts (AF) of annual earnings scaled by total assets per share. Analyst forecasts are obtained from IBES five months after the firm's fiscal year end. Characteristic forecasts are obtained on yearly basis where historically-fitted coefficients are estimated from an earnings regression using data from the prior calendar year and applied to firms' most recent characteristics. In Panel B, the dependent variables are REV and IMB. REV is realized difference the final consensus forecast and the consensus measured prior to the portfolio formation date, scaled by total assets per share. IMB equals the average difference in the number of upward and downward buy/sell recommendation revisions, scaled by the total number of forecast revisions during the window between the portfolio formation date and the firm's earnings announcement. All control variables are assigned to quintiles ranging from 0 to 1 using breakpoints from the prior calendar year. SIZE equals the log of market capitalization and BTM equals the book-to-market ratio. ACC equals total accruals scaled by total assets. MOMEN equals the market-adjusted return over the six months prior to the portfolio formation. LTG is the consensus long-term growth forecast in IBES. t-statistics are shown in parentheses and are based on two-way clustered standard errors by year and industry. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level. The sample used in this analysis consists of 51,591 firm-years spanning 1980-2009.

Panel A: Realized Forecast Errors

	BIAS		IBIAS	
CO	–	0.176***	–	0.110***
	–	(7.38)	–	(5.52)
SIZE	0.307***	0.311***	0.266***	0.268***
	(5.47)	(5.56)	(5.29)	(5.27)
BTM	0.038	-0.001	-0.005	-0.011
	(1.10)	(-0.06)	(-0.16)	(-0.56)
MOMEN	0.290***	0.285***	0.240***	0.239***
	(6.96)	(7.27)	(6.45)	(6.70)
ACC	-0.085***	-0.073***	-0.069***	-0.064***
	(-3.85)	(-3.59)	(-3.92)	(-3.96)
LTG	-0.139***	-0.124***	-0.099***	-0.091***
	(-4.64)	(-4.93)	(-4.87)	(-4.76)
Intercept	-0.354***	-0.407***	-0.266***	-0.324***
	(-3.85)	(-5.93)	(-3.35)	(-5.13)
Adj. R^2 (%)	7.345	8.142	7.053	7.479

Panel B: Forecast and Recommendation Revisions

	REV		IMB	
CO	–	0.074***	–	0.097***
	–	(4.68)	–	(7.79)
SIZE	0.223***	0.224***	0.073***	0.071***
	(5.59)	(5.48)	(3.43)	(3.47)
BTM	0.004	0.009	-0.044	-0.017
	(0.18)	(0.62)	(-1.52)	(-0.75)
MOMEN	0.212***	0.212***	0.089***	0.094***
	(7.06)	(7.30)	(5.01)	(5.10)
ACC	-0.052***	-0.051***	-0.051***	-0.053***
	(-3.79)	(-3.78)	(-3.54)	(-3.38)
LTG	-0.068***	-0.065***	-0.058***	-0.055***
	(-4.13)	(-3.96)	(-3.23)	(-3.59)
Intercept	-0.233***	-0.284***	-0.071	-0.170***
	(-3.78)	(-5.48)	(-1.62)	(-6.10)
Adj. R^2 (%)	7.887	8.200	0.987	1.289

Table 4: Realized Returns by Quintiles of CO

Panel A (B) presents future raw (market-adjusted) returns by quintiles of CO. CO is defined as the difference in characteristic forecasts (CF) and analyst forecasts (AF) of annual earnings scaled by the firm's total assets per share. Analyst forecasts are obtained from IBES as the most recent mean consensus forecast available five months following the firm's fiscal year end. Characteristic forecasts are obtained on yearly basis where historically-fitted coefficients are estimated from an earnings regression using data from the prior calendar year and applied to firms' most recent characteristics. RR(X,Y) and RET(X,Y) equal the cumulative raw and market-adjusted return accumulated from month X to month Y following the portfolio formation date. Market-adjusted returns are calculated as the raw cumulative return minus the CRSP value-weighted return as reported in CRSP over the same holding period. t-statistics are based on Monte Carlo simulations by forming annual empirical reference distributions that randomly assign all firms to quintiles, by matching the observational counts in each CO quintile. I simulate 1,000 portfolios for each year and calculate the average long-short difference for each simulated portfolio. I calculate and report average bootstrap t-statistics by contrasting the realized annual hedge returns against the empirical reference distributions. The sample used in this analysis consists of 51,591 firm-years spanning 1980-2009.

Panel A: Future Raw Returns

	RR(1,6)	RR(1,12)	RR(13,24)	RR(1,24)
1 (Low CO)	0.024	0.106	0.125	0.221
2	0.034	0.136	0.152	0.287
3	0.044	0.145	0.144	0.294
4	0.049	0.162	0.155	0.315
5 (High CO)	0.049	0.163	0.153	0.316
High-Low	0.025	0.058	0.029	0.095
Bootstrap t-statistic for H_0: High-Low=0	6.422	8.602	4.138	8.837

Panel B: Future Market-Adjusted Returns

	RET(1,6)	RET(1,12)	RET(13,24)	RET(1,24)
1 (Low CO)	-0.023	-0.011	0.007	-0.017
2	-0.015	0.018	0.034	0.047
3	-0.001	0.028	0.025	0.053
4	0.003	0.042	0.038	0.074
5 (High CO)	0.003	0.041	0.038	0.077
High-Low	0.026	0.053	0.031	0.094
Bootstrap t-statistic H_0: High-Low=0	7.042	8.271	4.816	9.016

Table 5: Cross-Sectional Return Regressions

The table below presents regressions results of six- and twelve-month future realized returns. RET(X,Y) is cumulative market-adjusted return accumulated from month X to month Y following the portfolio formation date. All control variables are assigned to quintiles ranging from 0 to 1 using breakpoints from the prior calendar year. CO equals the difference between characteristic forecasts (CF) and analyst forecasts (AF) of annual earnings scaled by the firm's total assets. Analyst forecasts are obtained from IBES as the prevailing forecast five months following the firm's fiscal year end. Characteristic forecasts are obtained on yearly basis where historically-fitted coefficients are estimated from an earnings regression using data from the prior calendar year and applied to firms' most recent characteristics. SIZE equals the log of market capitalization and BTM equals the book-to-market ratio. MOMEN equals the market-adjusted return over the six months prior to the portfolio formation. ACC equals total accruals scaled by total assets. LTG is the consensus long-term growth forecast in IBES. PEAD is the firm's most recent earnings surprise, defined as the firm's actual earnings minus the IBES consensus forecast immediately prior to the announcement and scaled by price. VTP is the fundamental value estimate derived from analyst forecasts, scaled by equity share price. t-statistics are shown in parentheses and are based on two-way clustered standard errors by year and industry. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level. The sample used in this analysis consists of 51,591 firm-years spanning 1980-2009.

Panel A: Regression Results of RET(1,6)

	(1)	(2)	(3)	(4)	(5)	(6)
CO	–	–	0.028***	0.020***	0.021***	0.023***
	–	–	(3.83)	(3.20)	(3.28)	(3.23)
CF/TA	–	0.046***	–	–	–	–
	–	(4.47)	–	–	–	–
AF/TA	-0.003	-0.040***	–	–	–	–
	(-0.26)	(-3.61)	–	–	–	–
SIZE	-0.001	-0.003	-0.004	-0.018	-0.018	-0.017
	(-0.05)	(-0.18)	(-0.27)	(-1.48)	(-1.46)	(-1.36)
BTM	0.028	0.029	0.022	0.007	0.008	0.003
	(1.22)	(1.25)	(1.11)	(0.46)	(0.54)	(0.30)
MOMEN	0.075***	0.077***	0.077***	0.072***	0.067***	0.067***
	(4.82)	(4.93)	(4.82)	(4.65)	(4.10)	(4.31)
ACC	–	–	–	-0.031***	-0.029***	-0.030***
	–	–	–	(-3.12)	(-3.06)	(-3.11)
LTG	–	–	–	-0.031	-0.031	-0.032
	–	–	–	(-1.59)	(-1.57)	(-1.58)
PEAD	–	–	–	–	0.029***	0.029***
	–	–	–	–	(3.32)	(3.32)
VTP	–	–	–	–	–	0.008
	–	–	–	–	–	(0.54)
Intercept	-0.056***	-0.061***	-0.068***	-0.016	-0.032*	-0.035**
	(-2.62)	(-2.78)	(-3.20)	(-1.02)	(-1.84)	(-2.00)
Adj. R^2 (%)	0.694	0.779	0.787	1.007	1.112	1.116

Panel B: Regression Results of RET(1,12)

	(1)	(2)	(3)	(4)	(5)	(6)
CO	–	–	0.036***	0.027**	0.029***	0.039***
	–	–	(3.52)	(2.46)	(2.59)	(3.57)
CF/TA	–	0.085***	–	–	–	–
	–	(5.09)	–	–	–	–
AF/TA	0.018	-0.051***	–	–	–	–
	(1.45)	(-2.73)	–	–	–	–
SIZE	-0.006	-0.010	-0.011	-0.026	-0.026	-0.020
	(-0.32)	(-0.52)	(-0.61)	(-1.55)	(-1.56)	(-1.30)
BTM	0.078*	0.079*	0.056	0.041	0.043*	0.011
	(1.87)	(1.92)	(1.49)	(1.61)	(1.67)	(0.62)
MOMEN	0.103***	0.106***	0.103***	0.097***	0.089***	0.095***
	(3.28)	(3.37)	(3.30)	(3.16)	(2.72)	(2.92)
ACC	–	–	–	-0.051***	-0.049***	-0.051***
	–	–	–	(-3.69)	(-3.59)	(-3.86)
LTG	–	–	–	-0.026	-0.026	-0.031
	–	–	–	(-0.75)	(-0.74)	(-0.83)
PEAD	–	–	–	–	0.044***	0.044***
	–	–	–	–	(2.82)	(2.82)
VTP	–	–	–	–	–	0.053**
	–	–	–	–	–	(2.02)
Intercept	-0.073**	-0.082***	-0.070**	-0.009	-0.033	-0.050**
	(-2.55)	(-2.89)	(-2.28)	(-0.32)	(-1.27)	(-2.32)
Adj. R^2 (%)	0.596	0.712	0.650	0.811	0.910	0.996

Table 6: Additional Return Analysis

Panel A reports equal-weighted four-factor regression results of monthly returns from a long (short) position in the highest (lowest) quintile of characteristic forecast optimism. CO is defined as the difference in characteristic forecasts (CF) and analyst forecasts (AF) of annual earnings scaled by the firm's total assets. Analyst forecasts are obtained from IBES as the prevailing forecast available five months following the firm's fiscal year end. Characteristic forecasts are obtained on yearly basis where historically-fitted coefficients are estimated from an earnings regression using data from the prior calendar year and applied to firms' most recent characteristics. Firms are assigned to quintiles of CO five months following the firm's fiscal year end and held for periods of six and twelve months. Panel A presents the intercept from estimating the following pooled regression over the entire sample window:

$$R_{CO,m} = \alpha + \beta_1(R_{mkt,m} - R_{f,m}) + \beta_1 HML_m + \beta_2 SMB_m + \beta_3 UMD_m + \epsilon_{i,m}$$

where $R_{CO,t}$ is the hedge return obtained from buying (selling) firms in the highest (lowest) quintile of CO in month t, $R_{f,t}$ is the risk free rate, $R_{mkt,t} - R_{f,t}$ equals the excess return on the market, HML equals the return on the high-minus-low book-to-market strategy, SMB equals the hedge return on the small-minus-big strategy, and UMD equals the hedge return on the up-minus-down momentum strategy. All factors are obtained from Ken French's website. Panel B contains regression results of future market-adjusted returns during the firm's next two quarterly earnings announcements. The dependent variable in columns (5) and (6) equals the average announcement return over the subsequent two earnings announcements. SIZE is defined as the log of market capitalization and BTM is defined as the book-to-market ratio. MOMEN equals the market-adjusted return over the six months prior to the portfolio formation. ACC is defined as the total accruals scaled by total assets. LTG is the consensus long-term growth forecast in IBES. The sample used in this analysis consists of 51,591 firm-years spanning 1980-2009.

Panel A: Fama-French Factor Regressions

	Six-Month Holding Period			Twelve-Month Holding Period		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.526***	0.418***	0.446***	0.379***	0.252**	0.237**
	(3.28)	(2.91)	(3.06)	(2.94)	(2.28)	(2.11)
MKT-RF	-0.269***	-0.147***	-0.155***	-0.280***	-0.167***	-0.163***
	-(7.78)	-(4.45)	-(4.60)	-(10.11)	-(6.63)	-(6.30)
SMB	–	-0.217***	-0.216***	–	-0.131***	-0.132***
	–	-(4.56)	-(4.53)	–	-(3.56)	-(3.58)
HML	–	0.364***	0.350***	–	0.388***	0.396***
	–	(7.35)	(6.90)	–	(10.17)	(10.09)
UMD	–	–	-0.036	–	–	0.021
	–	–	-(1.17)	–	–	(0.86)

Panel B: Future Earnings Announcement Window Returns

	1st Qtr.		2nd Qtr.		1st & 2nd Qtrs.	
CO	0.338***	0.196**	0.178	0.106	0.249***	0.143**
	(3.67)	(2.08)	(1.59)	(0.94)	(4.42)	(2.04)
SIZE	–	0.026	–	0.097	–	0.038
	–	(0.21)	–	(0.71)	–	(0.40)
BTM	–	0.170	–	0.208*	–	0.184
	–	(0.90)	–	(1.75)	–	(1.44)
MOMEN	–	0.466**	–	0.294***	–	0.380***
	–	(2.56)	–	(2.66)	–	(3.59)
ACC	–	-0.336***	–	-0.478***	–	-0.415***
	–	(-3.13)	–	(-2.98)	–	(-4.88)
LTG	–	-0.395*	–	0.060	–	-0.164
	–	(-1.76)	–	(0.46)	–	(-1.54)
Intercept	0.011	0.124	-0.094	-0.145	-0.022	0.025
	(0.14)	(0.57)	(-0.79)	(-0.69)	(-0.40)	(0.14)
Adj. R^2 (%)	0.024	0.142	0.006	0.072	0.024	0.179

Table 7: Conditional Strategy Returns

The panels below present future one-year ahead market-adjusted returns based on a two-way independent sort by quintiles of CO and terciles of a given firm characteristic. CO is defined as the difference in characteristic forecasts (CF) and analyst forecasts (AF) of annual earnings scaled by the firm's total assets per share. Characteristic forecasts are obtained on yearly basis where historically-fitted coefficients are estimated from an earnings regression using data from the prior calendar year and applied to firms' most recent characteristics. SELL/HOLD/BUY are dummy variables that equal one if the average IBES concensus buy/sell recommendation is above 2.5, between 2.5 and 1.25, and below 1.25, respectively. SIZE is defined as the log of market capitalization and BTM is defined as the book-to-market ratio. ABAC is defined as the absolute value of total accruals scaled by total assets. PEAD is the firm's most recent earnings surprise, defined as the firm's actual earnings minus the IBES consensus forecast immediately prior to the announcement and scaled by price. t-statistics are based on Monte Carlo simulations by forming annual empirical reference distributions that randomly assign all firms to quintiles, by matching the observational counts in each CO quintile. I simulate 1,000 portfolios for each year and calculate the average long-short difference for each simulated portfolio. I calculate and report average bootstrap t-statistics by contrasting the realized annual hedge returns against the empirical reference distributions. The sample used in this analysis consists of 51,591 firm-years spanning 1980-2009.

Panel A: RET(1,12) by Quintiles of CO and Terciles of REC

	1 (SELL)	2 (HOLD)	3 (BUY)
1 (Low CO)	0.030	0.010	-0.023
2	0.025	0.031	0.016
3	0.030	0.021	0.037
4	0.040	0.041	0.052
5 (High CO)	0.047	0.045	0.071
High-Low	0.017	0.035	0.094
Bootstrap t-statistic for H_0: High-Low=0	3.375	5.401	7.681

Panel B: RET(1,12) by Quintiles of CO and Terciles of SIZE

	1 (Low SIZE)	2 (Mid SIZE)	3 (High SIZE)
1 (Low CO)	-0.009	-0.001	0.002
2	0.015	0.029	0.014
3	0.040	0.035	0.016
4	0.046	0.040	0.035
5 (High CO)	0.057	0.039	0.004
High-Low	0.066	0.039	0.002
Bootstrap t-statistic for H_0: High-Low=0	5.765	4.095	0.578

Panel C: RET(1,12) by Quintiles of CO and Terciles of BTM

	1 (Low BTM)	2 (Mid BTM)	3 (High BTM)
1 (Low CO)	-0.017	0.002	-0.013
2	0.024	0.013	0.018
3	0.026	0.019	0.038
4	-0.009	0.039	0.058
5 (High CO)	0.015	0.051	0.064
High-Low	0.032	0.049	0.077
Bootstrap t-statistic for H_0: High-Low=0	3.490	3.702	4.366

Table 7 [Continued]: Conditional Strategy Returns

Panel D: RET(1,12) by Quintiles of CO and Terciles of ABAC

	1 (Low ABAC)	2 (Mid ABAC)	3 (High ABAC)
1 (Low CO)	0.031	0.029	-0.052
2	0.033	0.039	-0.017
3	0.032	0.036	0.014
4	0.041	0.053	0.026
5 (High CO)	0.036	0.049	0.044
High-Low	0.006	0.019	0.096
Bootstrap t-statistic for H_0: High-Low=0	0.801	2.655	7.173

Panel E: RET(1,12) by Quintiles of CO and Terciles of PEAD

	1 (Low PEAD)	2 (Mid PEAD)	3 (High PEAD)
1 (Low CO)	-0.046	-0.016	0.031
2	-0.015	0.005	0.049
3	-0.002	0.008	0.053
4	0.005	0.031	0.065
5 (High CO)	0.031	0.037	0.055
High-Low	0.077	0.053	0.025
Bootstrap t-statistic for H_0: High-Low=0	8.250	5.579	3.386

Table 8: Multivariate Return Regressions and Interaction Effects

The table contains interaction effects from regressions where the dependent variable is, RET(1,12), one-year ahead market-adjusted returns. All firms are assigned to quintiles of characteristic forecast optimism (CO) five months following the firm's fiscal year end, using quintile breakpoints from the prior calendar year. CO is defined as the difference in characteristic forecasts (CF) and analyst forecasts (AF) of annual earnings scaled by the firm's total assets. Analyst forecasts are obtained from IBES as the prevailing forecast available five months following the firm's fiscal year end. Characteristic forecasts are obtained on yearly basis where historically-fitted coefficients are estimated from an earnings regression using data from the prior calendar year and applied to firms' most recent characteristics. SIZE is defined as the log of market capitalization and BTM is defined as the book-to-market ratio. BUY is a dummy variable that equal one if the average IBES concensus buy/sell recommendation is below 1.25. ABAC is defined as the absolute value of total accruals scaled by total assets. PEAD is the firm's most recent earnings surprise, defined as the firm's actual earnings minus the IBES consensus forecast immediately prior to the announcement and scaled by price. LowSize is a dummy variable corresponding to the lowest SIZE tercile and HighMTB is a dummy variable corresponding to the highest MTB tercile. The remaining interaction variables are defined analogously. Main effects are included in the regression but omitted from the table. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level. The sample used in this analysis consists of 51,591 firm-years spanning 1980-2009.

	(1)	(2)	(3)	(4)	(5)	(6)
CO	0.024**	0.006	0.020*	-0.001	0.018	-0.033**
	(2.19)	(0.54)	(1.87)	(-0.07)	(1.57)	(-2.15)
CO*BUY	0.111***	–	–	–	–	0.088**
	(3.73)	–	–	–	–	(2.58)
CO*LowSIZE	–	0.066***	–	–	–	0.041*
	–	(3.58)	–	–	–	(1.89)
CO*LowMTB	–	–	0.032	–	–	0.024
	–	–	(1.44)	–	–	(0.98)
CO*HighABAC	–	–	–	0.088***	–	0.081***
	–	–	–	(3.72)	–	(3.24)
CO*LowPEAD	–	–	–	–	0.039**	0.032*
	–	–	–	–	(2.34)	(1.87)
BUY	-0.066**	-0.019	-0.020	-0.019	-0.020	-0.055**
	(-2.40)	(-0.85)	(-0.86)	(-0.82)	(-0.85)	(-1.97)
LowSIZE	0.011	-0.022	0.012	0.012	0.012	-0.009
	(1.21)	(-1.38)	(1.30)	(1.26)	(1.31)	(-0.52)
LowMTB	0.022	0.022	0.003	0.022	0.022	0.008
	(0.97)	(0.97)	(0.10)	(1.00)	(0.98)	(0.28)
HighABAC	-0.044***	-0.044***	-0.045***	-0.086***	-0.045***	-0.082***
	(-4.40)	(-4.38)	(-4.42)	(-5.17)	(-4.42)	(-4.75)
LowPEAD	-0.043***	-0.042***	-0.043***	-0.043***	-0.064***	-0.060***
	(-4.57)	(-4.48)	(-4.55)	(-4.57)	(-5.29)	(-4.72)
Intercept	0.025*	0.034**	0.026*	0.039**	0.028*	0.054***
	(1.67)	(2.45)	(1.66)	(2.37)	(1.87)	(3.39)
Adj. R^2 (%)	0.465	0.487	0.445	0.526	0.451	0.596

Table 9: Comparison to Traditional Approach

The table reports regression results of analyst forecast errors (BIAS), revisions (REV), and future market-adjusted returns (RET(1,12)) on quintiles of CO and additional controls. BIAS is defined as realized difference between earnings as reported in Compustat and the prevailing consensus forecast, scaled by total assets per share. REV is realized difference the final consensus forecast and the consensus measured prior to the portfolio formation date. RET(1,12) is the firm's twelve-month market-adjusted return starting five months following the firm's fiscal year end. All control variables are assigned to quintiles ranging from 0 to 1 using breakpoints from the prior calendar year. CO equals the difference in characteristic forecasts (CF) and analyst forecasts (AF) of annual earnings scaled by total assets per share. Analyst forecasts are obtained from IBES five months after the firm's fiscal year end. Characteristic forecasts are obtained on yearly basis where historically-fitted coefficients are estimated from an earnings regression using data from the prior calendar year and applied to firms' most recent characteristics. PFE is the predicted forecast error obtained by regressing realized forecast errors on the same variables used to create characteristic forecasts, where historically-fitted coefficients are applied to a firm's most recent firm-characteristics. SIZE is defined as the log of market capitalization and BTM is defined as the book-to-market ratio. MOMEN equals the market-adjusted return over the six months prior to the portfolio formation. ACC is defined as the total accruals scaled by total assets. LTG is the consensus long-term growth forecast in IBES. PEAD is the firm's most recent earnings surprise, defined as the firm's actual earnings minus the IBES consensus forecast immediately prior to the announcement and scaled by price. t-statistics are shown in parentheses and are based on two-way clustered standard errors by year and industry. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level. The sample used in this analysis consists of 51,591 firm-years spanning 1980-2009

	BIAS		REV		RET(1,12)	
	(1)	(2)	(3)	(4)	(5)	(6)
CO	–	0.175***	–	0.076***	–	0.030***
	–	(7.29)	–	(4.63)	–	(2.70)
PFE	0.099***	0.082**	0.047*	0.039	-0.010	-0.013
	(2.97)	(2.42)	(1.92)	(1.59)	(-0.32)	(-0.42)
SIZE	0.285***	0.283***	0.210***	0.209***	-0.017	-0.018
	(4.52)	(4.67)	(4.55)	(4.63)	(-0.94)	(-0.97)
BTM	0.022	-0.008	0.021	0.008	0.052*	0.047
	(0.88)	(-0.33)	(1.20)	(0.47)	(1.86)	(1.65)
MOMEN	0.238***	0.248***	0.183***	0.187***	0.090***	0.091***
	(6.23)	(6.52)	(6.56)	(6.71)	(2.69)	(2.74)
ACC	-0.088***	-0.072***	-0.057***	-0.050***	-0.052***	-0.049***
	(-3.88)	(-3.44)	(-3.97)	(-3.67)	(-3.56)	(-3.50)
LTG	-0.138***	-0.109***	-0.069***	-0.056***	-0.031	-0.026
	(-4.57)	(-4.10)	(-3.52)	(-3.27)	(-0.90)	(-0.74)
PEAD	0.142***	0.151***	0.098***	0.102***	0.041***	0.042***
	(3.25)	(3.48)	(3.25)	(3.42)	(2.60)	(2.73)
Intercept	-0.409***	-0.507***	-0.304***	-0.347***	-0.017	-0.033
	(-4.94)	(-6.09)	(-4.91)	(-5.60)	(-0.66)	(-1.16)
Adj. R^2 (%)	8.203	8.995	8.660	8.997	0.859	0.900

Table 10: Comparison to Existing Forecast Error Models

The table reports regression results of analyst forecast errors (BIAS), revisions (REV), and future market-adjusted returns (RET(1,12)) on quintiles of CO and additional controls. BIAS equals the realized difference between Compustat earnings and the prevailing consensus forecast, scaled by total assets per share. REV is realized difference the final consensus forecast and the consensus measured prior to the portfolio formation date. All control variables are assigned to quintiles ranging from 0 to 1 using breakpoints from the prior calendar year. CO equals the difference in characteristic forecasts (CF) and analyst forecasts (AF) of annual earnings scaled by total assets per share. Analyst forecasts are obtained from IBES five months after the firm's fiscal year end. Characteristic forecasts are obtained on yearly basis where historically-fitted coefficients are estimated from an earnings regression using data from the prior calendar year and applied to firms' most recent characteristics. $\widehat{FE}^T$ is the predicted forecast error obtained by using the methodologies of Frankel and Lee (1998) and Hughes, Liu, and Su (2008). SIZE is defined as the log of market capitalization and BTM is defined as the book-to-market ratio. MOMEN equals the market-adjusted return over the six months prior to the portfolio formation. ACC is defined as the total accruals scaled by total assets. LTG is the consensus long-term growth forecast in IBES. PEAD is the firm's most recent earnings surprise, defined as the firm's actual earnings minus the IBES consensus forecast immediately prior to the announcement and scaled by price. t-statistics are shown in parentheses and are based on two-way clustered standard errors by year and industry. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level. The sample used in this analysis consists of 46,834 firm-years spanning 1981-2009.

Panel A: Comparison to Hughes, Liu, and Su (2008)

	BIAS			REV			RET(1,12)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CO	–	–	0.181***	–	–	0.081***	–	–	0.027**
	–	–	(7.56)	–	–	(5.00)	–	–	(2.35)
$\widehat{FE}^T$	0.194***	0.074	0.069	0.127***	0.052	0.050	0.034	0.002	0.001
	(3.67)	(0.96)	(0.86)	(3.74)	(1.02)	(0.95)	(1.29)	(0.06)	(0.03)
SIZE	0.279***	0.276***	0.270***	0.189***	0.194***	0.191***	-0.008	-0.010	-0.011
	(4.32)	(3.84)	(3.91)	(4.43)	(3.93)	(3.97)	(-0.55)	(-0.68)	(-0.77)
BTM	0.095***	0.035	0.002	0.055***	0.027	0.012	0.063	0.047*	0.042
	(3.13)	(1.40)	(0.07)	(3.04)	(1.57)	(0.71)	(1.64)	(1.83)	(1.58)
MOMEN	0.186***	0.204***	0.216***	0.149***	0.158***	0.164***	0.083**	0.087**	0.089**
	(4.36)	(4.27)	(4.40)	(5.03)	(4.81)	(4.86)	(2.15)	(2.23)	(2.27)
ACC	–	-0.083***	-0.066***	–	-0.053***	-0.046***	–	-0.052***	-0.050***
	–	(-3.59)	(-3.10)	–	(-3.63)	(-3.28)	–	(-3.36)	(-3.31)
LTG	–	-0.144***	-0.112***	–	-0.071***	-0.057***	–	-0.031	-0.026
	–	(-3.97)	(-3.44)	–	(-3.13)	(-2.79)	–	(-0.86)	(-0.71)
PEAD	–	0.132***	0.143***	–	0.093***	0.098***	–	0.031*	0.033**
	–	(2.80)	(3.03)	–	(2.98)	(3.17)	–	(1.89)	(2.03)
Intercept	-0.495***	-0.371***	-0.477***	-0.340***	-0.284***	-0.331***	-0.070**	-0.022	-0.038
	(-6.06)	(-4.50)	(-5.76)	(-6.29)	(-4.61)	(-5.37)	(-2.39)	(-1.07)	(-1.53)
Adj. R^2 (%)	6.985	7.985	8.849	7.798	8.652	9.040	0.685	0.933	0.973

Panel B: Comparison to Frankel and Lee (1998)

	BIAS			REV			RET(1,12)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CO	–	–	0.181***	–	–	0.083***	–	–	0.024*
	–	–	(5.85)	–	–	(4.13)	–	–	(1.70)
$\widehat{FE}^T$	0.124***	0.073	0.002	0.055**	0.026	-0.006	0.030	0.020	0.010
	(3.24)	(1.42)	(0.03)	(2.10)	(0.75)	(-0.17)	(0.95)	(0.60)	(0.27)
SIZE	0.342***	0.304***	0.299***	0.238***	0.214***	0.212***	0.001	-0.010	-0.011
	(5.14)	(4.86)	(5.01)	(5.25)	(4.89)	(4.98)	(0.03)	(-0.63)	(-0.68)
BTM	0.137***	0.073**	0.002	0.077***	0.040*	0.008	0.072*	0.057*	0.048
	(4.40)	(2.20)	(0.06)	(4.09)	(1.89)	(0.34)	(1.71)	(1.97)	(1.45)
MOMEN	0.277***	0.234***	0.245***	0.209***	0.180***	0.185***	0.099***	0.087***	0.089***
	(6.60)	(6.24)	(6.43)	(6.80)	(6.57)	(6.66)	(3.16)	(2.65)	(2.70)
ACC	–	-0.085***	-0.069***	–	-0.055***	-0.048***	–	-0.052***	-0.050***
	–	(-3.64)	(-3.34)	–	(-3.75)	(-3.56)	–	(-3.40)	(-3.44)
LTG	–	-0.112***	-0.125***	–	-0.065**	-0.071***	–	-0.019	-0.021
	–	(-2.66)	(-3.04)	–	(-2.37)	(-2.63)	–	(-0.54)	(-0.61)
PEAD	–	0.156***	0.160***	–	0.108***	0.110***	–	0.033**	0.034**
	–	(3.58)	(3.68)	–	(3.80)	(3.89)	–	(2.49)	(2.54)
Intercept	-0.555***	-0.446***	-0.473***	-0.367***	-0.309***	-0.321***	-0.084**	-0.043	-0.047
	(-6.99)	(-4.59)	(-5.03)	(-7.01)	(-4.43)	(-4.70)	(-2.09)	(-1.03)	(-1.11)
Adj. R^2 (%)	6.861	8.019	8.792	7.458	8.610	8.976	0.702	0.948	0.977