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A new approach to predicting analyst forecast errors: Do investors overweight analyst forecasts?☆

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ABSTRACT

I provide evidence that investors overweight analyst forecasts by demonstrating that prices do not fully reflect predictable components of analyst errors, which conflicts with conclusions in prior research. I highlight estimation bias in traditional approaches and develop a new approach that reduces this bias. I estimate characteristic forecasts that map current firm characteristics into forecasts of future earnings. Contrasting characteristic and analyst forecasts predicts analyst forecast errors and revisions. I find abnormal returns to strategies that sort firms by predicted forecast errors, consistent with investors overweighting analyst forecasts and predictable biases in analyst forecasts influencing the information content of prices.

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.

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[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).

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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) conclude 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 a reflection 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 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, assessing whether investors overweight analyst forecasts is difficult 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 relations 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 term reflects the fact that I contrast analysts' earnings forecasts with characteristic forecasts of earnings, in which 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 investment 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 could 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 metric that I refer to as characteristic forecast optimism, defined as the ex ante characteristic forecast minus the prevailing consensus forecast, in which higher values correspond to firms whose characteristics signal future earnings that exceed analyst projections. I find 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. 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.

[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 details.

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 investors' 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 be concerned not only with how distortions in analyst forecasts differentially impact the welfare of subsets of investors (e.g., retail versus 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 with two existing forecast error prediction models and again find evidence favoring the use of the characteristic approach.

The rest of the paper is organized as follows. Section 2 provides motivation for predicting analyst forecast errors and discusses traditional approaches. Section 3 discusses the related literature. Sections 4 and 5 discuss the empirical tests, findings, and robustness checks. Section 6 concludes.

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 $X_{1,j,t-1} \ldots X_{M,j,t-1}$ 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 $X_{1,j,t-1} \ldots X_{M,j,t-1}$. 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 $X_{1,j,t-1} \ldots X_{M,j,t-1}$, and $Z_{1,j,t-1} \ldots Z_{K,j,t-1}$ denote analysts' private information and incentives to bias forecasts. This representation of analyst forecasts is motivated by a substantial literature showing the role of competing interests in shaping analyst outputs (see Section 3 for further discussion). For example, Z_i could denote private information obtained from firms' management or pressure from analysts' employers to issue favorable forecasts. Combining Eqs. (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 firm characteristics, $X_{1,j,t-1} \ldots X_{M,j,t-1}$. Eq. (3) demonstrates that the error from this regression equals

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

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 Eq. (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 Eq. (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, $\Omega_{j,t}$ could 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, $\Omega_{j,t}$ could 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 Eq. (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 $(\beta_i - \gamma_i)$

[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), and Hughes, Liu, and Su (2008).

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:

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

where the T-superscript indicates that the predicted forecast error is calculated under the traditional approach. 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 conditional upon the correlations between $FE_{j,t+1}$, $X_{i,j,t-1}$, and $Z_{i,j,t-1}$. For a given $Z_{i,j,t-1}$, $\widehat{FE}^{T}_{j,t+1}$ could 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.

Bias in the estimated coefficients results from researchers' inability to observe inputs to analyst forecasts, denoted by $Z_{i,j,t-1}$ in Eq. (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 researcher to identify all inputs influencing analyst forecasts. Moreover, even if researchers are 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 Eq. (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 could 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 Eq. (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:

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

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 errors results in biased estimates that could be above or below the realized forecast error. The direction and magnitude of the bias depends on the correlation between observable characteristics used to predict analyst errors and unobservable inputs to analyst forecasts. Under the assumptions outlined above, bias in the traditional approach is largely avoidable using the characteristic approach. However, the relative efficacy of the characteristic approach depends on the reasonableness of these assumptions and must be tested empirically. Section 3 discusses the motivation for the characteristic approach in the context of the existing literature. Section 4 outlines the empirical implementation and contrasts the predictive power of the characteristic and traditional approaches.

3. Relation to literature

This study relates to three primary streams of literature. The first stream of literature shows that the information that analysts provide significantly influences the market's assessment of firm value. A second stream 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 find 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, Kim, Krische, and Lee, 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.

[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, $X_{1,j,t-1} \ldots X_{M,j,t-1}$. *(footnote continued)* If this assumption is not certain to hold, both approaches could 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.

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), Dechow, Hutton, and Sloan (2000), and Hong and Kubik (2003) find that analysts face incentives to provide optimistic forecasts and recommendations to secure lucrative investment banking relationships. Similarly, Francis and Philbrick (1993), Lim (2001), and Libby, Hunton, Tan, and Seybert (2008) demonstrate that analysts' desire for access to management results in biased forecasts and recommendations. Supporting this view, related work by Groysberg, Healy, and Maber (2011) uses proprietary data on analysts' annual compensation and finds no evidence that forecast inaccuracy negatively impacts analysts' pay. Additional studies find that biases result from analysts' incentives to generate trading revenue and institutional clientele (e.g., Hayes, 1998; Irvine, 2004), asymmetric responses to negative and positive news (e.g., Easterwood and Nutt, 1999), underreaction to past news (e.g., Lys and Sohn, 1990; Abarbanell, 1991; Mendenhall, 1991; Ali, Klein, and Rosenfeld, 1992), over extrapolation of past trends (e.g., Bradshaw, 2004), and the overweighting of private information (e.g., Chen and Jiang, 2006). Collectively, this literature finds that ignoring predictable analyst biases 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) find 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) find 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 finds that prices tend 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; Ivkovic and Jegadeesh, 2004; Jegadeesh, Kim, Krische, and Lee, 2004). Similarly, Womack (1996) and Barber, Lehavy, McNichols, and Trueman (2001) demonstrate that the returns of firms with favorable recommendations outperform those with unfavorable recommendations. Frankel and Lee (1998) show that differences between prices 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 forecast errors instead of investment 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 or 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 forecast errors contributes to more precise tests of how investors weight the information that analysts provide (see Appendix A and Section 4 for 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 short period of time, which makes tests of overweighting less sensitive to research design problems such as survivorship or omitted variable biases that could 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 by using publicly available signals. For example, Bradshaw, Richardson, and Sloan (2001) show that analyst forecasts do not reflect the implications of high accruals for changes in future earnings and Bradshaw, Richardson, and Sloan (2006) show that analysts underreact to the implications of external financing on firms' profitability. Similarly, Ali, Klein, and Rosenfeld (1992), Elgers and Lo (1994), Lo and Elgers (1998), Gode and Mohanram (2009), and Konchitchki, Lou, Sadka, and Sadka (2011 use the traditional approach to create predicted analyst forecast errors and demonstrate that analysts underreact to publicly observable signals.

[5] The idea that investors ignore predictable analyst errors is directly related to the literature finding that security prices fail to fully reflect large sample properties of earnings and earnings changes. For example, Ou and Penman (1989), Piotroski (2000), and Piotroski and So (2012) 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.

Dechow, Hutton, and Sloan (1999) provide an empirical assessment of the residual income model and find that although firms' book values are incrementally useful in forecasting future earnings relative to analyst forecasts, estimates of firm value that ignore the implications of book value for future earnings explain more of the cross-sectional variation in stock prices. Dechow, Hutton, and Sloan (1999) reconcile these findings by providing evidence that security prices underreact to differences between analyst forecasts and autoregressive forecasts that utilize the implications of book values for future earnings.

Related work by Frankel and Lee (1998) uses 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' growth forecasts.[6] They provide some evidence consistent with the existence of predictable analyst errors that are not reflected in stock prices in a timely fashion, though the statistical significance of these findings is mixed. 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. 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 in this paper suggests that the conclusions of Hughes, Liu, and Su (2008) are a reflection of their methodology, which can result in unnecessary noise in their estimates of predicted analyst forecast errors.

4. Empirical tests

As outlined in Section 2, the characteristic approach to predicting analyst forecast errors involves comparing analyst forecasts with characteristic forecasts estimated from past firm characteristics. The process of calculating characteristic forecasts mimics the construction of $\hat{E}_{j,t+1}$ in Eq. (7) and follows closely from the procedures developed in Fama and French (2006) and Hou, van Dijk, and Zhang (2012). This section provides details on the implementation of the characteristic approach and discusses the results of the main empirical tests.

4.1. Estimating characteristic forecasts and sample selection

Creating characteristic forecasts requires selecting a set of firm characteristics used in the prediction of future earnings. Any publicly observable firm characteristic could be used and, hence, an infinite set of possible permutations exists. 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. Specifically, I estimate the following cross-sectional regression for all firms reporting earnings in calendar year t:

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

where the subscripts indicate that earnings are regressed on lagged characteristics. The dependent variable is a firm's earnings per share ($E_{j,t}$). Philbrick and Ricks (1991) and Bradshaw and Sloan (2002) note that the Institutional Brokers' Estimates System (IBES) earnings and analyst forecasts often omit non-recurring items that are included in Generally Accepted Accounting Principles (GAAP) earnings. Bradshaw and Sloan (2002) note that special items account for most of the discrepancies between the two earnings numbers. To facilitate a comparison between the two forecasts, I define earnings throughout the analyses as net income before extraordinary items after subtracting special items multiplied by 0.65, where the 0.65 reflects an assumed tax rate of 35% as in Bradshaw and Sloan (2002).

Following Fama and French (2006), Eq. (9) expresses earnings in year t as a linear function of the following lagged firm characteristics from year $t-1$: earnings per share when earnings are positive and zero otherwise (E_j^+), 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 (BTM_j) defined as book value scaled by market value of equity, and end of fiscal year share price ($PRICE_j$).[7]

Prior research uses firm-specific time series models to forecast future quarterly earnings (e.g., Foster, 1977; Watts and Leftwich, 1977; O'Brien, 1988). I use cross-sectional characteristic forecasts instead of time-series forecasts for three reasons. First, time-series forecasts commonly assume that earnings follow an autoregressive integrated moving average (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, Hagerman, Griffin, and

[6] 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 (2012) for discussions of this practice.

[7] In Section 5.1, I discuss the results of estimating variants of Eq. (9) that exclude characteristics involving price as well as separate tests that use analyst forecasts to predict future earnings. Similarly, I also estimate the earnings forecast model of Hou, van Dijk, and Zhang (2012) and reestimate Eq. (9) when using a continuous version of E_j^+ instead of left-truncating lagged earnings at zero. These variations lead to qualitatively similar results.

Zmijewski, 1987; O'Brien, 1988; Dechow, Hutton, and Sloan, 1999), 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; Hou, van Dijk, and Zhang, 2012).

I estimate Eq. (9) for each firm-year in Compustat that possesses 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 Eq. (9). The regression coefficients indicate that firms with higher past earnings and dividends, non-loss firms, firms with low 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 Eq. (9), I apply historically estimated coefficients to current firm characteristics such that characteristic forecasts are available on an ex ante basis,

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 (*BTM*), share price (*PRICE*), a dummy variable indicating negative earnings (*NEGE*), earnings before extraordinary items adjusted for special items left-truncated at zero (E^+), absolute accruals per share when accruals are negative and zero otherwise (ACC^-), accruals per share when accruals are positive and zero otherwise (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 the Institutional Brokers' Estimates System (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 a 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% levels, respectively. The sample used in this analysis consists of 51,591 firm-years spanning 1980–2009.

Panel A: Earnings regressions

Variable	Description	Average coefficient	Average *t*-statistic
Intercept		0.232	3.053
E^+	Earnings per share	0.672	27.469
NEGE	Loss indicator	−0.631	−9.279
ACC^-	Neg. accruals per share	0.014	0.754
ACC^+	Pos. accruals per share	−0.028	−1.931
AG	Asset growth	−0.093	−3.060
DD	Dividend indicator	−0.065	−1.335
BTM	Book-to-market	−0.053	−0.197
PRICE	Share price	0.010	4.767
DIV	Dividend per share	0.130	3.092
Average Adj. R^2		0.561	

Panel B: Correlations and average forecast errors

	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 (RE)

	(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

prior to observing realized FY1 earnings. The year t characteristic earnings forecast for firm j equals

$$CF_{j,t} \equiv \hat{\beta}_0 + \hat{\beta}_1 E^{+}_{j,t} + \hat{\beta}_2 NEGE_{j,t} + \hat{\beta}_3 ACC^{-}_{j,t} + \hat{\beta}_4 ACC^{+}_{j,t} + \hat{\beta}_5 AG_{j,t} + \hat{\beta}_6 DD_{j,t} + \hat{\beta}_7 DIV_{j,t} + \hat{\beta}_8 BTM_{j,t} + \hat{\beta}_9 PRICE_{j,t}, \tag{10}$$

where $\hat{\beta}$ denotes the coefficients obtained from estimating Eq. (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 consensus forecasts (LTG) in the IBES Unadjusted Summary file within the three months prior to the portfolio formation date.[8] I use the IBES Unadjusted Summary 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.

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, the characteristic forecast described by Eq. (10) mirrors the construction of $\hat{E}_{j,t+1}$. Thus, motivated by Eqs. (7) and (8), my empirical prediction of the consensus forecast error equals the difference between the characteristic and analyst forecasts. Specifically, I create a new variable, characteristic forecast optimism ($CO_{j,t}$), that I use as the primary means of ranking firms in cross-sectional tests. $CO_{j,t}$ 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 Eq. (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.[9] I scale the difference between characteristic and analyst forecasts by total assets instead of equity prices because, to the extent that equity prices reflect earnings expectations created by analyst forecasts, the numerator and denominator of CO could move in tandem, which can potentially induce spurious cross-sectional variation (Ball, 2011; Cheong and Thomas, 2011).[10]

Having defined CO in Eq. (11), it is helpful to review the paper's central predictions of how CO relates to analyst forecast errors and future stock returns. Regarding analyst forecast errors, Eq. (11) demonstrates that when CO is high, a firm's fundamentals signal future earnings that are likely to be high relative to the analyst forecast, and vice versa. Thus, higher values of CO should correspond to analyst forecasts that are overly pessimistic (i.e., realized earnings in excess of analyst forecasts) and lower values of CO should correspond to analyst forecasts that are overly optimistic (i.e., realized earnings that fall below analyst forecasts).

Similarly, regarding future returns, to the extent that investors naively benchmark their expectations of earnings to analyst forecasts and do not fully utilize information in firms' fundamentals, higher values of CO should correspond to higher future returns. This positive predicted relation between CO and future returns reflects the idea that higher (lower) values of CO portend positive (negative) future earnings news not yet reflected in price. These predictions are restated more formally in Empirical Prediction 1 and 2.

Empirical Prediction 1. Characteristic forecasts in excess of analyst forecasts predict realized earnings in excess of analyst forecasts. Thus, characteristic forecast optimism, CO, positively predicts analyst forecast errors (actual earning minus analyst forecasts of earnings).

Empirical Prediction 2. Characteristic forecasts in excess of analyst forecasts correlate positively with earnings information not fully reflected in current prices. Thus, characteristic forecast optimism, CO, positively predicts future abnormal returns.

To test the paper's central predictions, I merge the intersection of the Compustat and IBES databases with monthly return data from the Center for Research in Security Prices (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 time at which I assume all information needed to assign firms to tradable portfolios is publicly observable.

Fig. 1 provides the timeline of analysis for an example firm with a December 31 fiscal year-end 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 31 and all of the outcomes being predicted are observed after June 1. Enforcing a minimum five-month separation between firms' fiscal year-end and

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

[9] For example, suppose that Eq. (9) is estimated such that total earnings is scaled by two 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 three 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.

[10] In untabulated results, scaling CO by the absolute characteristic forecast in place of total assets produces qualitatively similar results. I use total assets in the main analyses to avoid potential scaling issues when the characteristic forecast of earnings is close to zero and to more closely mimic the structure of tests of the overweighting of analyst forecasts as outlined in Appendix A.

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.

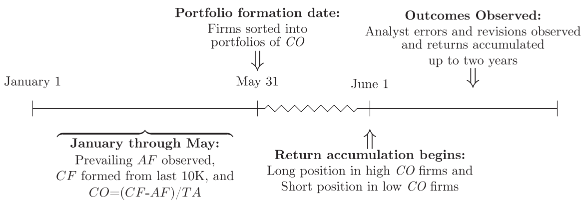

Fig. 1. Timeline of analysis. The figure contains a timeline of variable measurement used in the main analyses. The timeline uses firms with December 31 fiscal year-end as an example to emphasize that the empirical tests are constructed to avoid look ahead biases. All of the signals used for prediction are known prior to May 31 and all of the outcomes being predicted are observed after June 1. *CO* is defined as the difference in characteristic and analyst forecasts of annual earnings scaled by the firm's total assets. Analyst forecasts *AF* are obtained from the Institutional Brokers' Estimates System (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 *CF* are obtained on a 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.

Throughout the analysis, I eliminate financial firms with Standard Industrial Classification (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. Fig. 2 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

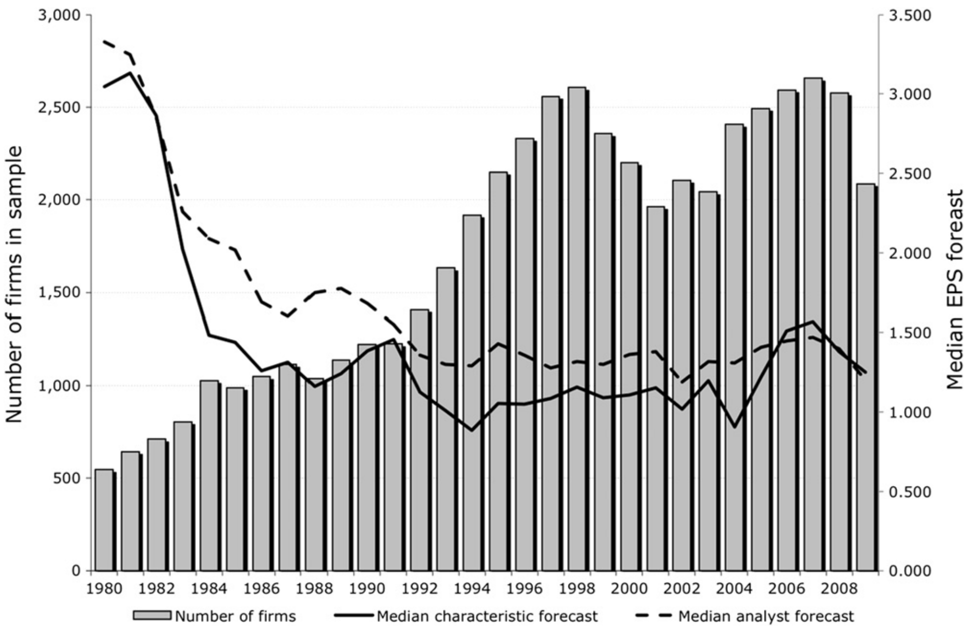

Fig. 2. Sample size by year. The figure plots the total number of firms and median characteristic and analyst earnings per share (EPS) forecasts for each calendar year in the sample window. Analyst forecasts (shown in the dashed black line) are obtained from the Institutional Brokers' Estimates System (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 a 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.

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 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 with characteristic forecasts.

4.2. *Predicting realized forecast errors and forecast revisions*

Panel A of Table 2 contains mean firm characteristics across *CO* quintiles. 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. *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. *DISP* is significantly higher for high *CO* firms for whom analysts are pessimistic relative to the characteristic forecasts, which is consistent with the findings in Welch (2000) that analyst pessimism is positively (negatively) related to the tendency to issue bold (herding) earnings forecasts. *COV*, the number of analysts covering the firm at the time of portfolio formation, varies in a statistically significant fashion across the extreme *CO* portfolios. However, the level of coverage differs across firms in the high and low *CO* portfolios by less than one analyst, suggesting that this difference might not be economically significant.

Panel B contains descriptive statistics across quintiles of *CO*. The first and second columns of Panel B contain the two main components of *CO*, characteristic forecasts and analyst forecasts per share. Although characteristic forecasts are significantly different across the extreme quintiles of *CO* the same is not true for analyst forecasts. The third and fourth columns of Panel B contain the average and standard deviation of *CO* across *CO* quintiles. The standard deviation of *CO* is larger in the extreme quintiles indicating that the distribution of *CO* possesses long tails. Panel C of Table 2 contains descriptive statistics of analyst forecast errors as measured by *BIAS*, which 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. Consistent with Empirical Prediction 1, the median of *BIAS* 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 monotonicity 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 C also contains the percentage of firm-years for which realized earnings are less than the analyst forecast and 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. 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. 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.

Table 2

Descriptive statistics by quintiles of characteristic forecast optimism.

Panels A and B presents descriptive statistics by quintiles of characteristic forecast optimism (*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 the Institutional Brokers' Estimates System (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 a 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. *SD*(*CO*) equals the standard deviation of *CO*. *SIZE* is defined as the log of market capitalization and *LBM* is defined as the log of book-to-market ratio. *DISP* equals the standard deviation of analyst forecasts and *COV* equals the number of analysts covering a firm at the time of portfolio formation. *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 C contains descriptive statistics of analyst forecast errors as measured by *BIAS*, which equals the difference between realized earnings (*RE*) 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 realized earnings, *RE*, are less than the analyst forecast and realized earnings, *RE*, are greater than the analyst forecast. The sample used in this analysis consists of 51,591 firm-years spanning 1980–2009.

Panel A: Mean firm characteristics by quintiles of CO

	SIZE	*LBM*	*DISP*	*COV*
1 (Low *CO*)	12.860	0.320	0.134	8.017
2	13.271	0.389	0.131	9.204
3	13.382	0.453	0.138	9.575
4	13.279	0.506	0.147	9.410
5 (High *CO*)	12.991	0.503	0.166	8.784
High–Low	0.131	0.183	0.032	0.768
p-value for H_0: High–Low = 0	0.190	0.000	0.003	0.044

Panel B: Summary statistics by quintiles of CO

	CF	*AF*	*CO*	*SD*(*CO*)
1 (Low *CO*)	0.942	1.747	−6.764	4.833
2	1.586	2.173	−2.111	0.424
3	1.866	2.331	−1.011	0.242
4	2.012	2.265	−0.263	0.206
5 (High *CO*)	1.966	1.552	2.023	2.455
High–Low	1.024	−0.196	8.787	−2.378
p-value for H_0: High–Low = 0	0.000	0.126	0.000	0.000

Panel C: Descriptive statistics of analyst errors by quintiles of CO

	Median *BIAS*	Mean *BIAS*	RE < AF	RE < 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	–	–

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.

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Table 3
Predicting forecast errors and revisions.

Panels A presents results from regressing realized forecast errors on quintiles of characteristic forecast optimism (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 the Institutional Brokers' Estimates System (IBES) five months after the firm's fiscal year-end. Characteristic forecasts are obtained on a 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% levels, respectively. 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

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 earnings per share (EPS) reported in IBES minus the June 30 consensus forecast and scaled by total assets per share. Columns 3 and 4 of Panel A contain qualitatively similar results when *IBIAS* is the dependent variable.

Panel B of Table 3 contains the regression results in which 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 investment recommendation revisions, scaled by the total 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 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 investment 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 could result in predictable risk-adjusted returns.

4.3. Testing the overweighting of analyst forecasts using realized 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

Table 4
Tests of the overweighting of analyst forecasts using realized returns.

This table presents future raw and market-adjusted returns by quintiles of characteristic forecast optimism (*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 the Institutional Brokers' Estimates System (IBES) as the most recent mean consensus forecast available five months following the firm's fiscal year-end. Characteristic forecasts are obtained on a 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 one thousand 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.

	Raw returns		Market-adjusted returns	
	RR(1,6)	*RR*(1,12)	*RET*(1,6)	*RET*(1,12)
1 (Low *CO*)	0.024	0.106	−0.023	−0.011
2	0.034	0.136	−0.015	0.018
3	0.044	0.145	−0.001	0.028
4	0.049	0.162	0.003	0.042
5 (High *CO*)	0.049	0.163	0.003	0.041
High–Low	0.025	0.058	0.026	0.053
Bootstrap *t*-statistic for H_0: High–Low=0	6.422	8.602	7.042	8.271

returns and differences between characteristic and analyst forecasts.[11] 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, Table 4 provide average realized returns for each *CO* quintile. Raw returns, denoted by *RR*(*X*,*Y*), 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*).

Consistent with Empirical Prediction 2, 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 one thousand 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 bootstrap *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. 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.[12] The main findings of Table 4 are unchanged when using market-adjusted returns, 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 12-month future returns in a multivariate setting. Panel A presents regression results in which the dependent variable equals market-adjusted returns over the six months following the portfolio formation date. For ease of interpretation, all

[11] Within the simple framework outlined in Appendix A, the conclusion that investors overweight analyst forecasts is reached if there exists 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 criterion. Though the main tests rely on characteristic forecasts specified by Eq. (10), Section 5.1 discusses the robustness of the paper's main findings to alternative earnings forecast models.

[12] Transaction costs are an important consideration when assessing the profitability of analyst-based investment strategy. For example, Barber, Lehavy, McNichols, and Trueman (2001) find that abnormal returns associated with analyst recommendations fail to exceed the transaction costs required to implement the investment strategy.

Table 5
Cross-sectional return regressions.

The table below presents regressions results of six- and 12-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. Characteristic forecast optimism (*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 the Institutional Brokers' Estimates System (IBES) as the prevailing forecast five months following the firm's fiscal year-end. Characteristic forecasts are obtained on a 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. *QSURP* 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% levels, respectively. 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)
QSURP	–	–	–	–	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)
QSURP	–	–	–	–	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

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 significantly positive relation with future returns, whereas analyst forecasts have a significantly 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 *CO* as the main predictive variable. I add 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, *CO* 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 *QSURP*, defined as the firm's most recent quarterly earnings minus the consensus forecast immediately prior to the announcement, and scaled by price. The results are qualitatively similar when controlling for standardized unexpected earnings in place of *QSURP*. Across columns 3 through 5, the *CO* coefficient remains statistically significant. 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 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.

Fig. 3 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

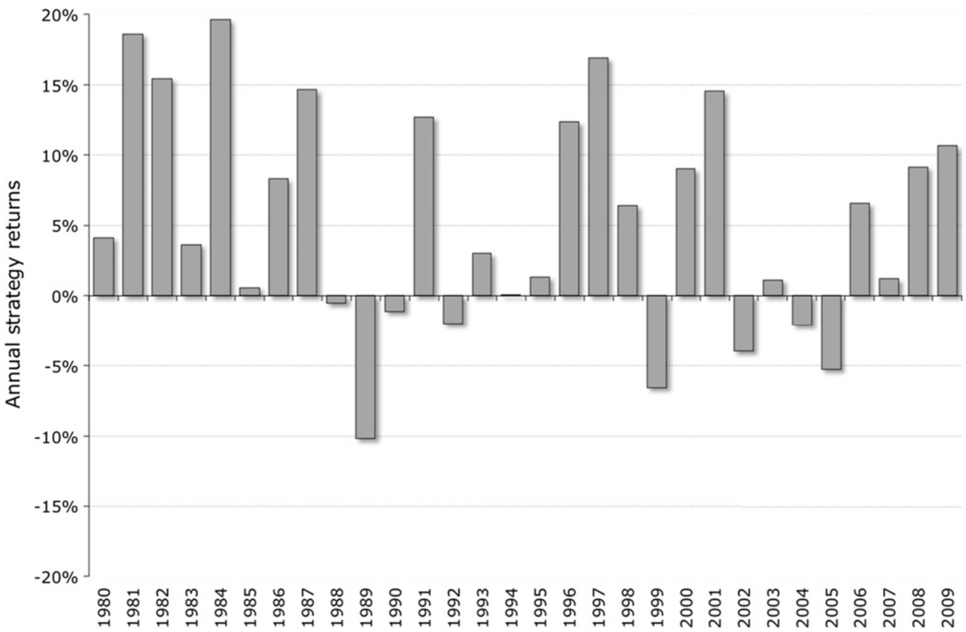

Fig. 3. Long-short strategy returns by year. The figure plots the annual difference in raw returns for firms in the highest and lowest quintiles of characteristic forecast optimism (*CO*). *CO* is defined as the difference in characteristic and analyst forecasts of annual earnings scaled by the firm's total assets. Analyst forecasts are obtained from the Institutional Brokers' Estimates System (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 a 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.

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 2008 and 2009. To the extent that strategy returns reflect compensation for bearing systematic risk, one could have expected the opposite result, namely, that returns are lowest during recessionary periods when investors' marginal utility for capital is highest.

4.4. Comparison of characteristic and traditional approaches

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 examine the predictive power of *CO* relative to two existing forecast error prediction models designed by Hughes, Liu, and Su (2008) and Frankel and Lee (1998). To match the *CO* portfolio formation date, I measure forecast errors five months following firms' fiscal year-end, defined as actual earnings minus the prevailing consensus estimate, scaled by total assets per share. Mirroring the construction of characteristic earnings forecasts, I historically estimate the relation between analyst forecast errors and the sets of variables described below. I then apply the resulting coefficients to firm characteristics in year t to obtain a predicted forecast error for year $t+1$ earnings. The Hughes, Liu, and Su (2008) model consists of fitting forecast errors to the following eight variables:

1. *ACC*: accruals scaled by total assets;
2. *LTG*: mean consensus long-term growth forecast;
3. *Sales Growth*: five-year percentage growth in sales;
4. ΔPPE: annual change of property, plant, and equipment;
5. ΔOLA: annual change of other long-term assets;
6. *QSURP*: the most recent analyst-based quarterly earnings surprise;
7. *RET*: market-adjusted stock returns over the past 12 months;
8. 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:

1. *Book-to-price*: book equity per share scaled by price;
2. *Sales Growth*: five-year percentage growth in sales;
3. *LTG*: mean consensus long-term growth forecast;
4. *OP*: $(V_f - V_W)/|V_W|$ 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 details).

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 6 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. Recall that *BIAS* equals the realized difference between Compustat earnings and the prevailing consensus forecast, and *REV* is realized difference the final consensus forecast and the consensus measured prior to the portfolio formation date, in which both variables are scaled by total assets per share. In both Panels A and B, column 1 demonstrates that $\widehat{FE}^T$ predicts analyst forecast errors incremental to *SIZE*, *BTM*, and *MOMEN*. However, $\widehat{FE}^T$ is no longer significant after controlling for the control variables used in Table 5: *ACC*, *LTG*, and *QSURP*. The insignificance of $\widehat{FE}^T$ 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.

In additional tests, I fit past forecast errors to the same firm characteristics used in Eq. (9) when constructing characteristic forecasts and again compare the predictive power of the two approaches. The results from these tests (untabulated) demonstrate that *CO* possesses significantly higher predictive power for analyst forecast errors, revisions, and future returns and are consistent with the methodological concerns associated with the traditional approach as outlined in Section 2.

4.5. The role of risk in driving predictable returns

An alternative interpretation of the positive *CO*-return relation is that return predictability manifests in response to priced risk correlated with *CO*. To mitigate concerns that *CO* reflects firms' sensitivities to known risk proxies, Panel A of Table 7 contains portfolio alphas from orthogonalizing *CO* strategy returns to the Fama-French and momentum factors (Fama and French, 1992, 1993):

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

where firms are assigned to quintiles once a year and held for periods of six and 12 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.

Table 6

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 characteristic forecast optimism (*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, scaled by total assets per share. 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 the Institutional Brokers' Estimates System (IBES) five months after the firm's fiscal year-end. Characteristic forecasts are obtained on a 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. *QSURP* 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% levels, respectively. 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)
QSURP	–	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)
QSURP	–	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

Table 7

Risk-adjustments and returns at subsequent earnings announcements.

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*). *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 the Institutional Brokers' Estimates System (IBES) as the prevailing forecast available five months following the firm's fiscal year-end. Characteristic forecasts are obtained on a 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 12 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

	First quarter		Second quarter		First and second quarters	
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

The intercept from estimating Eq. (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 of accessing whether a given signal reflects biased earnings expectations is to infer expectation errors implied by the market's response to earnings news (e.g., Bernard and Thomas, 1990; La Porta, Lakonishok, Shleifer, and Vishny, 1997). Panel B of Table 7 contains regression results of quarterly earnings announcement returns subsequent to the portfolio formation date. I obtain quarterly announcement dates from Compustat and calculate announcement window returns from $t-1$ to $t+1$, where t is the announcement date.

I find that *CO* positively 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 earnings announcement window. If the 5.3% strategy returns presented 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 returns during the second quarterly earnings announcement. Although the results in Panel B show 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.

4.6. Conditional tests of the overweighting of analyst forecasts

The preceding subsections establish a robust link between characteristic forecast optimism and future returns. A natural extension of Empirical Prediction 2 is to examine whether strategy returns are predictably concentrated among subsets of firms in which overweighting is ex ante more likely to occur and influence prices. Using *CO* as the predicted component of analyst errors, I predict that the *CO* strategy produces the largest returns among firms in which investors are more likely to overweight analyst forecasts and firms whose stock prices have higher sensitivities to earnings news. This is restated more formally as Empirical Prediction 3.

Empirical Prediction 3*. The relation between characteristic forecast optimism*, CO, *and future returns is strongest among firms in which investors are more likely to overweight analyst forecasts and firms whose stock prices have higher sensitivities to earnings news.*

I test Empirical Prediction 3 in three stages. First, I test the hypothesis that strategy returns are increasing in firms' stock price sensitivities to earnings news. Abarbanell and Lehavy (2003) provide evidence that investment recommendations reflect a collection of firms' incentives to meet or beat analyst forecasts, in which positive recommendations signal a higher sensitivity of firms' share prices to analyst-based earnings surprises.[13] Following Abarbanell and Lehavy (2003), I measure stock price sensitivity using firms' consensus buy/sell recommendation as of the portfolio formation date and predict that the *CO*-return relation is strongest among firms with the most positive recommendations. I obtain consensus investment recommendations from IBES, where ratings range from 1 = strong buy to 5 = strong sell. I divide the sample into three groups. Firms with a mean 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 consensus recommendation produces qualitatively similar results. Panel A of Table 8 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, in which the average annual return is 9.4% (t-statistic = 7.681). Although the *CO* strategy generates positive and statistically significant returns across each recommendation group, *CO* fails to predict economically significant returns in the *SELL* portfolio, consistent with the *CO*-return relation being stronger among firms with higher sensitivities to earnings news.

Second, I test the hypothesis that strategy returns are more concentrated among neglected firms in poor information environments. I use a firm's size as an inverse measure of the quality of its information environment and book-to-market ratio as a proxy for investor neglect. Panel B of Table 8 presents the time series average return for firms based on a two-way independent sort of *CO* and *SIZE*. Strategy returns are largest among small firms. This result is consistent with overweighting being concentrated among firms in poor information environments. Intuitively, this suggests that high information gathering costs could lead investors to rely more heavily on analysts as information intermediaries but is also consistent with mispricing being more pronounced in the presence of trading frictions. Panel C sorts firms based on *CO* and the book-to-market ratio. Although 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.

Further, I test the hypothesis that overweighting is more pronounced among firms with a high level of uncertainty regarding the relation between past and future performance. Following Hutton, Marcus, and Tehranian (2009), I use absolute accruals to measure the uncertainty regarding the mapping between current and future earnings, in which higher values indicate greater uncertainty. Thus, I predict that the *CO*-return relation is increasing in absolute accruals, reflecting investors being more likely to overweight analyst forecasts when financial statements are less transparent. Confirming this prediction, 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. Similarly, Panel E presents *CO* strategy returns across terciles of *QSURP*, 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,

[13] Abarbanell and Lehavy (2003) point out that the use of earnings response coefficients at earnings announcements can result in a stale measure of firms' stock price sensitivities to earnings news but empirically confirm that the two measures are positively correlated.

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Table 8
Conditional tests of the overweighting of analyst forecasts.

The panels below present future one-year ahead market-adjusted returns based on a two-way independent sort by quintiles of characteristic forecast optimism (*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 a 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 consensus investment recommendation is above 2.5, between 2.5 and 1.25, and below 1.25, respectively. Analyst recommendations are obtained from the Institutional Brokers' Estimates System (IBES). *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. *QSURP* 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 one thousand 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

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

Table 8 (*continued*)

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 QSURP

	1 (Low *QSURP*)	2 (Mid *QSURP*)	3 (High *QSURP*)
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

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.[14]

5. Robustness checks and discussion

This section outlines robustness checks of the main empirical tests as well as a discussion of the paper's central implications.

5.1. Robustness checks

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., Eqs. (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, in which 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 Eqs. (9) and (10) yields characteristic forecasts that are biased estimates of realized earnings but does not eliminate the ability of *CO* to predict future returns.

5.2. 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? Several non-mutually exclusive explanations for this pattern exist. 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, Hagerman, Griffin, and Zmijewski, 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 could face incentives to take positions that are justifiable *ex post*. Trading in line with consensus analyst forecasts may appear more prudent than trading against their recommendations and, thus, shield managers from legal culpability that arises from subsequent investment losses.

[14] I also examine the interaction effects shown in Table 8 within a multivariate regression. The untabulated results demonstrate that all of the interaction effects, except for *BTM*, remain significant in a multivariate setting, consistent with each conditioning variable capturing a distinct factor influencing the weights allocated to analyst forecasts.

Similarly, because the strategy employed in this paper relies on FY1 forecast errors, investors' investment horizons could 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 studied in the psychology 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 could 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; 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 investment 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 likely results 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 find 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. For example, returns are increasing in the sensitivity of firms' stock price to earnings news and the uncertainty between current and future earnings. 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 for 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

$$AF_j = \sum_{i=1}^{M} \beta_i \cdot X_{i,j} + P_j + B_j = AF^* + B_j, \tag{13}$$

where $X_{i,j}$ denotes a comprehensive set of M firm characteristics associated with the firm's future earnings, P_j denotes analysts' private information, B_j denotes analysts' incentive to bias their forecasts, and AF^* denotes analyst forecasts in the absence of incentives to bias their forecasts (i.e., $AF-B_j$). 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

$$CF_j = \sum_{i=1}^{M} \beta_i \cdot X_{i,j} = AF^* - P_j. \tag{14}$$

Assume that the distributions of analyst private information and incentives to bias are publicly known and given as $B_j \sim \mathrm{N}(\mu^{AF}, 1/\rho^{AF})$ and $P_j \sim \mathrm{N}(-\mu^{CF}, 1/\rho^{CF})$. The μ terms reflect the means each input and the ρ terms reflect their precisions. I assume that B_j is independent of P_j, which adds 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 characteristic and analyst forecasts:

$$OP_j \equiv \mathbf{E}_t[E_j | I_t] = \theta(CF_j - \mu^{CF}) + (1-\theta)(AF_j - \mu^{AF}), \tag{15}$$

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

Eq. (15) captures an intuitive relation between the optimal weights and the relative noise of characteristic 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 P_j 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, secure lucrative investment banking deals, and prevent analysts from issuing the optimal forecast, OP_j.

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

$$MK_j \equiv \delta(CF_j - \mu^{CF}) + (1-\delta)(AF_j - \mu^{AF}). \tag{16}$$

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 1. 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 Eq. (15). 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:

$$p_{j,t} = MK_j. \tag{17}$$

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

$$p_{j,t+1} - p_{j,t} \equiv r_j = E_j - MK_j, \tag{18}$$

where r_j is defined as the return from holding a share in firm j from period t to $t+1$.[15] 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

$$\mathbf{E}_t[r_j | I_t] = \mathbf{E}_t[E_j - MK_j] = 0. \tag{19}$$

Substituting Eqs. (15) and (16) into Eq. (19), expected returns can be expressed as

$$\mathbf{E}_t[r_j | I_t] = (\theta - \delta) \cdot (CF_j - \mu^{CF} - AF_j + \mu^{AF}). \tag{20}$$

Eq. (20) implies that expected returns are unrelated to the difference between de-meaned 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

[15] 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, Hughes, Liu, and Su (2008) model price changes as $p_{j,t+1} - p_{j,t} = \phi(E_j - MK_j)$, where ϕ is a positive constant.

$j \in L$. 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 Eq. (18), the difference in expected returns across the high and low portfolios can be expressed as

$$\bar{r}_H - \bar{r}_L = (\theta - \delta) \cdot \left[\frac{1}{N} \sum_{j \in H}^{N} (CF_j - AF_j) - \frac{1}{N} \sum_{j \in L}^{N} (CF_j - AF_j) \right]. \quad (21)$$

The portfolio-based approach characterized by Eq. (21) allows the researcher to look for evidence of overweighting without having to first estimate the average errors of the characteristic and analyst forecasts, μ^{AF} and μ^{CF}. Eq. (21) 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, $(\theta - \delta)$. The term inside the brackets within Eq. (21) is positive by construction. Hence, Eq. (21) 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 Eq. (21). I test whether sorting firms on the basis of CO 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 Eq. (21), 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

$$V_t = B_t + \frac{FROE_{t+1} - r_e}{(1+r_e)} B_t + \frac{FROE_{t+2} - r_e}{(1+r_e)^2} B_{t+1} + \sum_{i=3}^{T-1} \frac{FROE_{t+i} - r_e}{(1+r_e)^i} B_{t+i} + \frac{FROE_{t+T} - r_e}{r_e (1+r_e)^{T-1}} B_{t+T+1}, \quad (22)$$

where I assume that $T=12$ as in Gebhardt, Lee, and Swaminathan (2001) and furthermore 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, and $FROE_{t+i}$ is the forecasted return on equity (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 characteristic forecasts, I calculate one-, two-, and three-year ahead forecasts using Eqs. (9) and (10). 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. Finally, r_e is firms' cost of equity capital, assumed to be a fixed constant of 10%.

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