Identifying consensus analysts' earnings change forecasts with correct and incorrect signs.

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Abstract

This paper examines whether users of consensus analysts' earnings forecasts can exploit information in (a) the nature of analysts' historical forecast accuracy and firms' earnings predictability, and (b) fundamental analysis of firms' earnings growth to increase (reduce) the probability of relying on a consensus forecast which correctly (incorrectly) predicts the direction of the forthcoming annual earnings change. To increase (reduce) the reliance on consensus forecasts that correctly (incorrectly) predict the sign of the change in annual earnings, I develop two models to condition the consensus forecast. First, I develop a model that indicates the likelihood that the consensus analyst forecast correctly predicts the directional change based on analyst and firm characteristics. Second, I develop a model to indicate the likely sign of the earnings change using fundamental analysis. I find the conditioned forecasts significantly increase (reduce) the probability of correctly (incorrectly) predicting the sign of the annual change in earnings. I also find that implementing trading strategies based on the improved forecasts generates significant abnormal returns, which indicates the economic significance of relying on conditioned forecasts.

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1. INTRODUCTION

Can users of consensus analysts' earnings forecasts exploit information in (a) the nature of analysts' historical forecast accuracy and firms' earnings predictability, and (b) fundamental analysis of firms' earnings growth to segregate analysts' consensus forecasts of one-year-ahead earnings changes into those likely to be of the correct and incorrect sign? Market participants and researchers rely on analyst forecasts because analysts process and transform the information set in financial statements as well as additional information about the industry, firm strategy, and economy into future earnings predictions. Forecast users typically aggregate individual forecasts into a summary measure, referred to as a consensus forecast, to reduce the impact of individual idiosyncratic errors. I document in this study that consensus analysts' forecasts *incorrectly* predict the *sign* of the one-year-ahead change in annual earnings 23.2 percent of the time over the period 1991-2002 even though the consensus forecast relies on a broad information set and is likely to be relatively free of idiosyncratic error.

The two main objectives of this paper are (a) to investigate whether one can predict *ex ante* the cases in which the consensus analyst forecasts correctly and incorrectly predict the sign of the change in one-year-ahead earnings, and (b) to assess whether such predictions are associated with abnormal returns. To motivate my study, I first provide descriptive evidence that suggests that share prices seemingly unconditionally reflect the content of consensus analysts' forecasts of the sign of the change in earnings (i.e. share prices appear to assume the consensus forecasts are correct on average). In particular, I document that the average annual abnormal return generated by a trading strategy that goes long (short) in firms when analysts' forecast a one-year-ahead earnings increase (decrease) is essentially zero. This indicates that prices seem to reflect the information in consensus analysts' forecasts. However, a striking feature of this aggregate zero abnormal return arises when we segregate firms based on *ex post* knowledge (i.e. perfect foresight) of whether the consensus earnings growth forecasts are directionally correct or incorrect. In particular, the average abnormal returns for cases in which analysts predict an earnings increase (decrease) but the firm ultimately realizes an earnings decrease (increase) are -24.7 (37.8) percent. In addition, the average abnormal returns for cases in which analysts correctly predict an earnings increase (decrease) are 12.2 (-3.2) percent. This perfect foresight evidence raises the prospect that an *ex ante* approach that successfully distinguishes consensus analysts' forecasts of earnings changes with correct signs and incorrect signs could lead to an implementable investment strategy.

To develop such an approach, this paper examines whether users of consensus analysts' forecasts can *ex ante* assess the likelihood that the forecasts correctly predict the one-year-ahead earnings by conditioning on the characteristics of the analyst and firm associated with the forecast and conditioning on fundamental analysis of the firm itself. I first develop a model that assesses the likelihood that the consensus analyst forecast correctly predicts the directional change in forthcoming annual earnings based on analyst and firm characteristics. Then I develop a model that predicts the sign of the change in one-year-ahead earnings based on financial statement information. I examine the usefulness of the two sets of conditioning information separately and then together in a conditioning sequence. I develop two scoring systems to accomplish this, thereby linking one stream of accounting research that examines firm and analyst characteristics associated with forecast accuracy with another stream that examines predicting earnings with financial statement information.

My *analyst score* approach combines firm and analyst characteristics to measure the likelihood that the set of analysts that comprise the consensus forecast for a particular firm correctly forecast the sign of the change in one-year-ahead earnings. The consensus forecast may incorrectly predict the direction of the change in earnings because of analysts' errors and/or because firms' earnings may be inherently unpredictable. On one hand, firms may have relatively predictable earnings but the analysts make forecast errors through their inability or inexperience. Prior research finds systematic relations between analysts' forecast errors and analysts' characteristics.[1] On the other hand, analysts may perform to the best of their ability but unpredictable volatility in the firm's earnings process induces forecast error. Prior research

[1] See for example Mikhail et al. (1997, 2003), Clement (1999), Jacob et al. (1999), Lim (2001).

also finds systematic relationships between analyst forecast errors and firm characteristics.[2] Given the systematic relations that exist between forecast error and analyst and firm characteristics, one may be able to identify consensus forecasts *ex ante* that are more (or less) likely to correctly predict the sign of the change in one-year-ahead earnings.

I also develop a *fundamental score* approach in which I incorporate fundamental analysis to merge financial statement information into a firm-year-specific score of the likelihood of an earnings increase or decrease. Although analysts most likely perform fundamental analysis when developing earnings forecasts, they may not use all the information in financial statements. Abarbanell and Bushee (1997) examine analysts' use of fundamental signals and interpret their findings as evidence that analysts inefficiently use financial statement information. If analysts do not efficiently use past information, it suggests that earnings forecast users may be able to implement their own fundamental analysis to determine which consensus forecasts of the change in earnings will ultimately be of the correct and incorrect signs. Prior research finds financial statement information is not fully reflected in prices (Ou and Penman, 1989; Lev and Thiagarajan, 1993; Sloan, 1996; Beneish, 1999; Piotroski, 2000; Beneish, Lee, and Tarpley, 2001; Mohanram, 2004), but does not examine whether forecast users can improve upon the consensus forecasts. For example, Abarbanell and Bushee (1998) form investment portfolios based on fundamental signals without incorporating analysts' forecasts and find the portfolios generate significant abnormal returns but they do not examine whether an investor could use the fundamental signals to improve the forecasts. This paper extends this line of inquiry by determining whether investors can use their own fundamental analysis to augment analysts' apparent inefficient use of financial statement information.

I use the information in the *analyst score* and the *fundamental score* (separately and jointly) to assess the conditional likelihood that the consensus analysts' forecasts correctly predict the sign of the change in one-year-ahead earnings. I test the ability of the conditioned forecasts to distinguish between the forecasts that will *ex post* be right or wrong by examining the correct prediction percentage, defined as

[2] See for example Das et al. (1998), Lim (2001), Gu and Wu (2003).

the proportion of forecasts that correctly forecast the direction of the future earnings change. I then examine the abnormal returns associated with the conditioned forecasts and test whether the conditioning approach enables an investor to implement trading strategies that earn economically significant abnormal returns.

In general, the results suggest that conditioning the consensus analysts' forecasts of the sign of the change in one-year-ahead earnings on the analyst score and the fundamental score does significantly improve the forecast users' ability to predict *ex ante* which forecasts are likely to be directionally correct or incorrect. Further, the results suggest that the use of these predictions to identify directionally correct and incorrect forecasts relates to economically significant future abnormal returns.

More specifically, I document that the portfolios of consensus forecasts identified by the conditioning sequence as more (less) likely correct exhibit percentages of correct predictions that are greater than (less than) their respective benchmark percentages of correct predictions. For example, when analysts forecast earnings increases, the portfolio comprised of firm-year observations identified by the conditioning sequence as *more* likely correct exhibits an 85.9 percentage of correct predictions, an improvement of 9.1 percent over the unconditioned forecast's percentage of correct predictions, while the portfolio comprised of firm-year observations identified as *less* likely correct exhibits a 56.7 percentage of correct predictions, a deterioration of 20.1 percent from the unconditioned forecast's percentage of correct predictions. I then document that trading strategies based on the conditioning sequence's identification of more and less likely correct consensus forecasts generate positive abnormal returns. I predict and find that these results are stronger for a contrarian trading strategy that invests in firms for which the conditioning sequence identifies the consensus forecast as less likely correct, generating an average annual abnormal return of 30.1 percent.

My study is important to investors, researchers, and educators. Investors can use the findings and tools from this paper to adjust their reliance on consensus analysts' forecasts. The evidence in Dechow and Sloan (1997) suggests that stock prices naïvely incorporate biased analysts' forecasts of future growth. Jegadeesh et al. (2004) examine analysts' recommendations and find that analysts fail to incorporate the predictive power of signals that indicate future lower returns. Thus, an approach like the one developed in this paper that helps forecast users identify forecasts that do not fully incorporate financial statement information may allow an investor to avoid or exploit forecasts that are likely to have significant errors. The results are important to researchers that use analysts' consensus earnings forecasts in many research contexts, such as the market's expectations of future payoffs in empirical asset pricing studies (Frankel and Lee, 1998), a benchmark that managers try to achieve in earnings management studies (DeGeorge et al., 1999; Abarbanell and Lehavy, 2003), and as a proxy for uncertainty and consensus in information environment studies (Barron et al., 1998). Educators can use the results of this study by teaching future investment managers how to rely on financial statement analysis to highlight when analysts are more likely to make forecast errors and to help students avoid relying on potentially incorrect forecasts.

The remainder of the paper proceeds as follows. Section 2 provides the motivation and predictions. I detail the methodology in Section 3. Section 4 describes the sample selection procedures and data. Section 5 describes the tests and presents the results. Section 6 concludes.

2. MOTIVATION AND PREDICTIONS

In this study I ask whether users of consensus analysts' earnings forecasts can identify the forecasts that correctly (or incorrectly) predict the direction of the one-year-ahead earnings change with an assessment of the analysts and firm associated with the consensus analyst forecast and with simple fundamental analysis. To motivate the construction of my two models and develop my predictions, I draw upon two streams of accounting research: the analysts' forecast accuracy literature and the earnings prediction literature. The analysts' forecast accuracy literature identifies signals that may be useful in predicting *ex ante* which forecasts are more or less likely correct. The earnings prediction literature develops fundamental analysis models that identify signals that can be used to generate objective predictions of the sign of next year's earning change. I use the signals identified in each of these literatures to condition the consensus analysts' forecast and *ex ante* predict those forecasts that are more or less likely to correctly indicate the forthcoming directional earnings change.

In this analysis, I focus on identifying cases of correct and incorrect predictions of the *sign* of the change in one-year-ahead earnings rather than the magnitude. Many prior studies in this literature, including Ball and Brown (1968) and Ou and Penman (1989), also focus on the sign of the change in earnings. I make the research design choice to focus on this crude (but powerful) variable for selected reasons. First, the task of predicting the direction of a firm's future earnings change in the next year should be simpler than assigning a magnitude value to the earnings forecast. However, in my sample, the consensus analysts' forecasts incorrectly predict the *sign* of the future change in earnings 23.2 percent of the time. The incorrect sign forecasts represent a significant error because they miss the magnitude of earnings as well as the sign of the change in one-year-ahead earnings. Second, by focusing on the sign rather than the magnitude, I can measure my variables as dichotomies (earnings increase/decrease, sign correct/incorrect), and simplify the analysis and reduce measurement error (e.g., I can easily identify analysts' predicted sign and clearly determine whether their prediction was correct or incorrect).

First, I develop the analyst score model and the fundamental score model. I then describe the conditioning sequence and make predictions.

2.1 Analyst Score Model

In this subsection I rely on the extant literature's findings on analyst forecast error to identify factors associated with sell-side analysts' forecast accuracy and to develop an analyst forecast score, denoted AS, that *ex ante* predicts the likelihood that the consensus forecast correctly predicts the sign of the change in one-year-ahead earnings for a particular firm in a particular year. Prior studies commonly define forecast error as actual earnings less the earnings forecast (Mikhail et al, 1997; Clement, 1999; Gu and Wu, 2003) and identify two broad sources of forecast error – limitations in the analysts' forecast abilities and actual earnings predictability. I examine whether the determinants that distinguish superior forecasters and more predictable firms can be used to assess the likelihood that the consensus forecast correctly predicts the direction of the forthcoming earnings change. I apply the findings from the prior literature by focusing on when the consensus analyst forecast incorrectly predicts the sign of the change in one-year-ahead earnings.

Two other studies also use analyst or firm characteristics in *ex ante* prediction models. Brown and Mohd (2003) use individual analyst characteristics and forecast age to *ex ante* weight analysts' forecasts and construct two consensus forecasts of quarterly earnings. They find the accuracy of their analyst-characteristic weighted consensus forecasts is similar to their forecast-age weighted consensus forecasts. Based on these results they suggest it is more cost beneficial for users of analysts' forecasts to use a consensus forecast based on forecast age. However, their use of a short forecast horizon is likely to limit the predictive utility of individual analyst characteristics. When forecasting earnings over a short forecast horizon analysts likely use similar information and develop similar forecasts because a greater proportion of the information about the firm is public. Thus the short forecast horizon limits a forecast user's ability to distinguish analysts' accuracy. This paper extends this research by examining individual analyst characteristics that relate to a longer period (annual earnings) and a longer horizon (one-year-ahead) in order to more powerfully distinguish analysts' forecast accuracy.

Frankel and Lee (1999) develop a prediction model for analyst forecast errors using the book-to-market ratio, past sales growth, analyst long-term earnings growth forecast, and analyst optimism. They provide evidence of significant abnormal returns from a trading strategy that sells the shares of firms that are predicted to have the largest positive errors and buys the shares of firms that are predicted to have the lowest negative errors. Several key differences exist between this paper and Frankel and Lee (1999). First, their model predicts errors in three-year-ahead consensus earnings forecasts. An investor would have to take positions in firms for three years to capture the returns associated with the error, as evidenced by their strategy generating a 4.0 (27.7) percent return over 12 (36) months. I develop a one-year-ahead prediction model that allows investors to capitalize on analyst errors in a shorter period of time. Second, they use their model to identify forecasts that exhibit excessive optimism and pessimism while my model identifies forecasts that are likely correct and incorrect for both positive and negative predicted changes.

I develop expected relations between analyst and firm characteristics and CORRECT, an indicator variable that equals one when the consensus forecast correctly predicts the sign of the change in one-year-ahead earnings, and zero otherwise. I describe analyst characteristics first, firm characteristics second, and how I combine them last. Exhibit 1 summarizes the information content in each AS signal.

2.1.1. Analyst characteristics

I distinguish the more accurate forecasters of directional future earnings changes from the less accurate forecasters by developing proxies for analyst characteristics that have been shown to affect accuracy, such as experience, ability, available resources, and task complexity (Clement, 1999). I measure the attributes for each individual analyst and then average them across the analysts in the consensus to get a consensus-forecast measure. One of the purposes of aggregating individual forecasts into a consensus forecast is to reduce idiosyncratic error associated with individual analysts (O'Brien, 1988). In a consensus forecast, the individual characteristics associated with forecast error could cancel each other out when combined. Thus, my model will attempt to identify error in forecasts that already partially control for idiosyncratic error.

First, I calculate an analyst's firm-specific experience based on the number of years the analyst forecasted annual earnings for a particular firm prior to the current forecast.[3] I expect the consensus-forecast measure of experience (EXPER) to be positively related to CORRECT.

Second, I measure individual analysts' ability using historic forecast accuracy percentage, HFAP, by computing the percentage of correct forecasts of the sign of one-year-ahead earnings change based on all of an analyst's prior forecasts for all firms. This variable measures the relative frequency with which an analyst recognizes a year in advance whether the firm's earnings will increase or decrease.[4] I expect the consensus forecast measure of HFAP to be positively related to CORRECT.

[3] Mikhail et al. (1997) find three measures of analyst experience (firm-specific, industry specific, general) are all negatively related to forecast error. Clement (1999) finds a negative relation between forecast bias and firm-specific experience.

[4] I use this measure rather than forecast bias measures used in prior studies because it is better aligned with the purpose of the analyst forecast score in this study.

Prior studies use the number of analysts employed by a brokerage house as a proxy for the resources available to an analyst, and find it is negatively related to individual forecast error (Lim, 2001; Jacob et al., 1999; Clement, 1999). I use the size of the brokerage house an analyst works for to proxy for the resources available to the analyst, which I denote RES. I measure the size of the brokerage house each year by ranking them based on the number of analysts they employ that provide annual forecasts in the IBES database, placing them into deciles, and associating the decile-ranked measure with each analyst. I expect the consensus forecast measure of RES to be positively related to CORRECT.

As a proxy for task complexity, prior research utilizes the number of companies and industries an analyst follows and finds they are positively related to forecast error (Clement, 1999; Jacob et al, 1999). I measure the number of industries individual analysts follow in a given year using the IBES-defined industries. I expect the consensus forecast measure of the number of industries followed (TASK) to be negatively related to CORRECT.

2.1.2. Firm characteristics

Holding analyst characteristics constant, the sign of earnings changes can be more difficult to forecast for one firm than another firm. The difficulty arises from the firm's information environment and uncertainty about how available information relates to the firm's future prospects.

Prior research has used the number of analysts following the firm as a proxy for the richness of the firm's information environment and have found it relates negatively to forecast bias (Das et al., 1998; Lim, 2001; Mikhail et al., 1997). I measure the number of analysts (NUM) included in the consensus forecast each year. I expect NUM to be positively related to CORRECT.

To capture uncertainty in the firm's earnings environment, I use two factors. First, I measure the standard deviation of analysts' forecasts in the consensus, DISP. Barron et al. (1998) provide a theoretical basis for using forecast dispersion to measure uncertainty. I expect DISP to be negatively related to CORRECT. Second, I use the variability of the firm's earnings changes, VAR. I measure VAR as the standard deviation of operating income changes over the prior five years divided by the average standard deviation of earnings changes for the industry. I measure the industry average standard deviation by taking the average standard deviation of those firms within each 2-digit SIC code. I expect VAR to be negatively related to CORRECT.

Analysts' expectations of the sign of the change in earnings will more likely be correct as the magnitude of the predicted change become larger. I measure APRED as the absolute value of the consensus analysts' predicted change. I expect APRED to exhibit a positive relation to CORRECT.

2.1.3. Combining analyst and firm characteristics into an Analyst Score

In order to obtain an *ex ante* estimate of the likelihood that the consensus forecast of the one-year-ahead earnings change is correct, I estimate a logistic regression using CORRECT as the dependent variable. Each year I compute percentile ranks for each of the analyst and firm characteristics and use them as the independent variables.[5] I estimate a pooled logistic regression using a rolling period of up to five years prior to each forecast year to develop coefficient estimates for each of the characteristics. I then apply the coefficient estimates to the forecast year characteristics to get an *ex ante* measure (AS) of the likelihood the consensus forecast correctly predicts the sign of the one-year-ahead change in earnings.

2.2 Fundamental Score Model

The fundamental score (denoted FS) summarizes financial statement information into a single score that forecasts the sign of the one-year-ahead earnings change. Penman and Zhang (2002b) examine components of return on net operating assets (RNOA) to predict the one-year-ahead change in RNOA. I use Penman and Zhang's model to identify six fundamental analysis signals to incorporate into the summary FS measure. I assign points to each firm-year observation based on each signal's value, and then I sum the points across all the signals to compute each firm-year FS. The FS should be increasing in the likelihood that next year's earnings will increase. Exhibit 2 summarizes the information content each signal captures and how I measure and score each of the signals.

Current profitability provides a signal of future profitability. Economic theory suggests that the earnings a firm generates on its net operating assets, RNOA, will converge to a firm-specific mean over time. A firm with an extremely high RNOA is likely to encounter new competition and reduced future

[5] Frankel and Lee (1998) use a similar procedure in their analyst forecast error model.

returns, while a firm with an extremely low RNOA is likely to take steps to increase future returns or cease operations. Penman and Zhang (2002b) find current RNOA is negatively associated with future changes in RNOA. Based on this finding, I rank firms yearly using RNOA and place them into quintiles. I assign a point value of -1 to firms in the top quintile, 0 to firms in the middle three quintiles, and +1 to firms in the bottom quintile.

To provide further information about the future earnings change, I decompose RNOA into a profit margin and an asset turnover ratio, and further decompose profit margin into a gross margin ratio and a selling, general, and administrative expense ratio.

The gross margin ratio (computed as gross profit divided by sales) can provide information about firms' positions in input markets. Prior work asserts that when the gross margin ratio increases (decreases) at a rate faster than the rate of growth in sales, it signals potentially sustainable improvement (persistent deterioration) in the firm's relative pricing power in its product markets (Lev and Thiagarajan, 1993; Graham et al., 1962, p. 244). I measure the gross margin signal, GM, as the rate of change in the gross margin less the rate of change in sales. Abarbanell and Bushee (1997) find this GM signal relates positively to future earnings changes. I rank firm-year observations on the GM variable and place them into quintiles. I assign a point value of +1 (-1) to observations in the top (bottom) quintile and 0 to those in the middle three quintiles.

The next signal measures unusual changes in the selling, general, and administrative (SG&A) costs that support sales but are not directly involved in production. Anderson et al. (2003) assert that managers reveal private information about future changes in earnings through SG&A spending. Managers will maintain or increase SG&A if current period sales decrease and they believe the sales drop is temporary. They find a positive (negative) relation between SG&A and one-year-ahead earnings when sales decline (increase). Following Anderson et al. (2003) I measure the SG&A signal as the annual change in the ratio of SG&A costs over sales. To score SG&A, I first separate firm-year observations based on whether sales increase or decrease. Within each subset, I rank firms based on the SG&A signal and place them into quintiles. I assign a point value of +1 to firm-year observations when revenues increase (decrease) and the SG&A signal is in the lowest (highest) quintile. I assign a point value of -1 to firm-year observations when revenues decrease (increase) and the SG&A measure is in the lowest (highest) quintile. I assign a point value of 0 when the SG&A signal is in the middle three quintiles regardless of revenue increases / decreases.

The efficiency of a firm's operations affects current and future profitability. The asset turnover ratio (computed as sales divided by beginning total assets) measures how efficiently the firm utilizes assets in place to generate sales. An increase in the asset turnover ratio occurs when sales increase faster than net operating assets increase. If the increase is the result of increased operating efficiency and continues into the future, one should observe a positive relation between the asset turnover ratio and the future change in RNOA. If the increase is temporary, one should observe a negative relation between the asset turnover ratio and the change in RNOA. Penman and Zhang (2002b) find a positive relation between the annual change in the asset turnover ratio, denoted ATO, and future change in RNOA. I rank firm-year observations on the ATO measure and place them into quintiles. I assign a point value of +1 (-1) to observations in the top (bottom) quintiles and 0 to firms in the middle three quintiles.

The ATO variable incorporates information about the prior change in total assets but not the current change in net operating assets. The current change in net operating assets may also signal changes in future profitability. Accounting conservatism causes some types of investments to be expensed at a faster rate than economic reality, so current period investments may result in lower operating income in the earlier years of an asset's life and higher operating income in the latter years. I measure growth in net operating assets, G^{NOA}, as current period NOA less the average prior period NOA, divided by average prior period NOA. Penman and Zhang (2002b) reveal that G^{NOA} and RNOA interact to determine the sustainability of operating income and find G^{NOA} is negatively related to one-year-ahead RNOA so I score the signal based on a double-sort on RNOA and G^{NOA}. I first rank firm-year observations on RNOA and place them in quintiles. Within each RNOA quintile, I rank the observations on G^{NOA} and place them into quintiles. Within each RNOA quintile, I assign a point value of -1 (+1) to firms in the top (bottom) G^{NOA} quintile and 0 to firms in the middle three quintiles.

The growth in net operating assets consists of growth in cash investments and growth in operating accruals. Sloan (1996) investigates the accruals and cash flows components of operating income and finds cash flows are more persistent than accruals. Firms experiencing net operating income consisting primarily of income-increasing accruals may be more likely to experience future operating income decreases than firms experiencing net operating income from cash flows. I incorporate an accruals measure to capture the cross-sectional difference in earnings persistence. I measure accruals, denoted ACC, as accruals divided by average prior period NOA. Penman and Zhang (2002b) find a negative relation between accruals and $RNOA_1$. I score the ACC signal while controlling for current RNOA. I first rank firm-year observations on RNOA and assign them to quintiles. Within those quintiles I then rank firm-year observations by ACC and place them into quintiles. I assign a point value of -1 (+1) to firms in the top (bottom) ACC quintile within each RNOA quintile. I assign a point value of 0 to firms in the three middle quintiles.

Based on the scoring of these fundamental signals, FS may range from -6 to +6. More positive (more negative) scores indicate a future earnings increase (decrease) is more likely.

2.3 Conditioning Sequence

I use the conditioning information in AS and FS to partition the sample of forecasts into those that more or less likely correctly indicate the sign of the change in one-year-ahead earnings. I illustrate the conditioning sequence and likelihood assessments in Figure 1. The conditioning sequence consists of four steps. First, I split the sample based on the sign of the consensus analysts' forecasted change in earnings because prior studies have shown an optimism bias (O'Brien, 1988; Easterwood and Nutt, 1999) in analysts' forecasts, which implies for my study that analysts are less likely to be correct for earnings increases than for earnings decreases. Second, I split the sample based on the relative magnitude of the earnings change forecast because the forecast changes of larger absolute magnitude are more likely to have the correct sign. Firms with large (small) forecasted changes in one-year-ahead earnings have more (less) room to miss the magnitude of the forecasted change while still meeting the forecasted sign. Within each sign-based sample, I place forecasts into large, medium, or small terciles based on the magnitude of the forecasted change in earnings per share. I present the conditioning schema in Figure 1 for the general case and label the large, medium, and small terciles as L, M, and S, respectively.

After placing the forecasts into sub-samples based on sign and magnitude, I use AS to identify consensus forecasts that are more or less likely to correctly forecast the sign of the change in one-year-ahead earnings. I place consensus forecasts in the top (bottom) AS tercile in the more (less) likely correct groups. In the last step, I further condition the forecast using FS to indicate whether the firm's fundamentals suggest earnings are likely to increase or decrease in the following year. I categorize consensus forecasts in the top (bottom) FS quintile as more likely to experience an increase (decline) in earnings. In the next section I describe my predictions of the likelihood of the consensus analysts' forecast correctly predicting the forthcoming directional earnings change for four sets of firms by conditioning the consensus forecast on AS and FS.

2.4 Predictions

If the consensus analysts' forecast predicts an earnings increase (decrease), and AS indicates the forecast is likely to be directionally accurate, and FS indicates a likely earnings increase (decrease), I predict the analysts' forecast is *more* likely correct and the firm will experience an increase (decrease) in earnings. I place the firms for which the predicted increase is *more* likely correct into portfolios L1, M1, and S1. I place the firms for which the predicted decrease is *more* likely correct into portfolios L8, M8, and S8. These six portfolios (L1, M1, S1, L8, M8, S8) are formed by the conditioning sequence to include firms for which the consensus forecast is likely to be directionally correct. The premise of my paper is that share prices reflect the information in consensus analysts' forecasts so I do not expect that these portfolios will be associated with abnormal returns. In essence, these portfolios are formed on the basis that the market's expectations for the directional change in earnings is correct.

If the consensus analysts' forecast predicts an earnings increase (decrease) and AS indicates the forecast is less likely to be directionally accurate, and FS is contradictory (indicating a likely earnings decrease (increase)), I predict the analysts' forecast is *less* likely correct and the firm will experience a decrease (increase) in earnings. I place the firms for which the predicted increase is *less* likely correct into portfolios L4, M4, and S4. I place the firms for which the predicted decrease is *less* likely correct into portfolios L5, M5, and S5. If current share prices reflect the consensus forecast and if events occur within the subsequent year that invalidate the forecast, and if my conditioning procedure successfully isolates forecasts of earnings changes with incorrect signs, then these six portfolios (L4, M4, S4, L5, M5, S5) may be associated with abnormal returns. In effect, these portfolios are formed on the basis that the market's expectations for the direction of the change in earnings is incorrect, and that the market will correct its expectations over the next year.

I do not make any predictions in two situations which occur in both sign-based sub-samples because the signals provide mixed messages. In both situations, the analyst forecast accuracy model may have incorrectly assessed the accuracy of the consensus forecast or the fundamental analysis model may have incorrectly identified the sign of the firm's earnings change. The first situation occurs when AS suggests the forecast is more likely correct but FS indicates the earnings change will likely be in the opposite direction of the consensus forecast prediction. In figure 1, I label these portfolios as L2, M2, S2 and L7, M7, S7. The second situation occurs when AS suggests the forecast is less likely correct and FS indicates the earnings change will likely be in the same direction as the forecast. In figure 1, I label these portfolios as L3, M3, S3 and L6, M6, S6.

3. METHOD

I use AS and FS to identify the likelihood of the consensus forecast correctly predicting the directional forthcoming annual earnings change so the consensus analysts' forecast of the change in one-year-ahead earnings is a key variable of interest in this study. I define the consensus analysts' forecast as the median forecast made in the fourth month after prior fiscal year end. Analysts should have revised their forecasts of forthcoming annual earnings by this time based on the information in prior year's financial statements. I define the consensus prediction of the sign of the change in one-year-ahead earnings as the sign that results after subtracting the prior actual annual earnings.[6] I define the actual sign of the earnings change in the forecast year by subtracting prior actual earnings from reported actual earnings. I determine whether the consensus forecast correctly predicted the sign of the change in one-year-ahead earnings by comparing the predicted sign to the actual sign.

3.1 Prediction Performance Tests

I examine the conditioning sequence's ability to isolate forecasts that are more likely or less likely to correctly predict the directional change in forthcoming earnings within portfolios of forecasts based on the sign and magnitude of the predicted earnings change. To test the performance of the conditioning sequence, I compute a correct prediction percentage that equals the proportion of directionally correct forecasts to total forecasts. I derive the benchmark correct prediction percentages from the portfolios of unconditioned forecasts in large, medium, and small magnitude groups in each of the sign-based sub-samples. I compare the correct prediction percentages of the portfolios of conditioned forecasts to the correct prediction percentages of the unconditioned forecasts to determine whether my conditioning sequence identifies the consensus forecasts more or less likely to be correct relative to the respective benchmark. I also compute the difference between the correct prediction percentage of the more likely correct portfolio and the less likely correct portfolio to determine whether the conditioning sequence sufficiently distinguishes the likelihood of the forecasts being correct between the two portfolios.

For the portfolio of forecasts that the conditioning sequence identifies as *more* likely to be correct, I expect the percentages of correct predictions to *exceed* the percentages of correct predictions in the respective benchmark portfolios. For the portfolio of forecasts that the conditioning sequence identifies as *less* likely to be correct, I expect the percentages of correct predictions to be *lower than* the percentage of correct predictions in the respective benchmark portfolios. I calculate a z-statistic based on the binomial distribution to determine whether the percentage of correct predictions in the conditioned portfolios exceeds or is lower than the percentages of correct predictions in the unconditioned forecast

[6] I use the actual realized earnings values as reported by I/B/E/S to be consistent with I/B/E/S analysts' forecasts.

portfolios. I also expect the percentage of correct predictions in the portfolios of forecasts identified as more likely correct to be greater than the percentages of correct predictions in the portfolios of forecasts identified as less likely correct.

3.2 Economic Significance Tests

For the economic significance tests, I calculate abnormal returns by compounding the firm's raw return over a one-year holding period and then subtracting the return on the CRSP size-based decile portfolio to which the firm belongs for the same period. I begin the return cumulation period on the first day of the fifth month following fiscal year end because I measure the consensus forecast using analysts' forecasts made in the fourth month. This allows the market time to incorporate revisions of analysts' forecasts into their valuations. I end the cumulation period on the last day of the fourth month following the subsequent fiscal year end, and thereby capture price movements caused by investors reacting to information and events during the year that confirm or refute their beliefs about the firm's performance. If a firm delists, I include the delisting return in the calculation of the returns, place the funds available after delisting into the size-based decile, and continue cumulating returns through the end of the period.

I examine the economic significance of the improved forecast accuracy by devising two trading strategies based on the conditioning sequence. The first strategy, the strong strategy, invests in the firms for which the conditioning sequence identifies the consensus analysts' forecast as *more* likely correct. This strategy takes long (short) positions in the firms for which the conditioned forecast agrees with the analysts' forecast of an increase (decrease) in earnings. Because the premise of my paper is that the market relies on analysts' forecasts, on average, when making investment decisions and the conditioning sequence identifies these forecasts as the ones more likely to predict the directional earnings change correctly, I do not expect this strategy to generate positive abnormal returns. This strategy should only produce positive abnormal returns if the market does not fully reflect the analysts' forecast of the directional change in forthcoming earnings and does not completely process and impound information about the likelihood the forecasts are correct.

I devise the second strategy, the contrarian strategy, to capture the returns that result from the market's reliance on consensus analysts' forecasts that turn out to be directionally incorrect. This strategy invests in firms for which the conditioning sequence identifies the consensus analysts' forecasts as *less* likely correct. The strategy takes long (short) positions in the firms for which the conditioned forecast disagrees with the analysts' forecast of a decrease (increase) in earnings. I expect this strategy to produce positive abnormal returns if the market incorporates analysts' forecasts without efficiently processing and impounding information about the likelihood that the forecasts are correct. I predict that abnormal returns are more likely to be realized by the contrarian strategy than the strong strategy because the contrarian strategy predicts the market will be surprised by the actual sign of the earnings change, which is more likely to be associated with abnormal returns.

To provide a benchmark for assessing the magnitude of returns to the conditioning sequence strategies, I calculate the returns generated by an (unconditional) analysts' forecast strategy and a perfect foresight strategy. The (unconditional) analysts' forecast strategy takes long (short) positions in the firms for which analysts forecast an earnings increase (decrease). The perfect foresight strategy takes long (short) positions in the firms that *ex post* realize an earnings increase (decrease).

I measure the returns to each of these trading strategies using an approach similar to Bernard and Thomas (1990). I estimate the following regression to simulate a zero-investment portfolio:

$$AR_{jt+1} = b_0 + b_1 HEDGE_{jt} + e_{jt} \qquad (1)$$

AR represents abnormal returns measured as the monthly return less the size-adjusted decile return. In Figure 1, I label the investment positions that I use to assign values to $HEDGE_{jt}$. I code $HEDGE_{jt}$ as one when the conditioning sequence indicates taking a long position in the firms in the portfolio and zero when the conditioning sequence indicates taking a short position in the firms in the portfolio. Given that the regressors only take values of zero or one, I interpret the slope coefficient, b_1, in the regression equation as the return to a zero-investment hedge portfolio (Bernard and Thomas, 1990). I also provide data on the number of years the trading strategies generate positive abnormal returns.

To further my understanding of the economic significance of the conditioning sequence, I also examine the average abnormal returns generated by portfolios of firms for which the conditioning sequence identified the directional earnings change prediction as more or less likely correct within each sign-based sample. For predicted increases, I expect the more (less) likely correct portfolio to generate positive (negative) abnormal returns. For predicted decreases, I expect the more (less) likely correct portfolio to generate negative (positive) abnormal returns. I compare the average abnormal returns for these portfolios to the following two benchmarks: (1) zero abnormal return, and (2) the average abnormal return for the unconditioned portfolios of predicted increases/decreases. Again, my predictions are stronger for the portfolios formed on consensus forecasts that are less likely to be directionally correct because I expect the actual earnings changes for firms in these portfolios to surprise the market. If the conditioning sequence effectively aids the identification of earnings change forecast that are of the correct and incorrect sign, then the more and less likely correct portfolios are likely to experience significantly different future abnormal returns. Thus, I also examine whether the average abnormal returns are significantly different between the more and less likely correct portfolios.

4. SAMPLE AND DATA

The sample consists of all firms with available analyst, financial statement, and return data to calculate the consensus forecast of one-year-ahead earnings, construct AS and FS, and measure holding period returns, during the years 1990 to 2002.[7] I construct the analyst forecasts of the sign of the change in one-year-ahead earnings using the Institutional Broker Estimate System (I/B/E/S) Detail file. I use forecasted and actual earnings from I/B/E/S to determine the predicted and actual change in earnings. I gather annual financial statement data from Compustat. For returns tests, I obtain stock prices, returns, and market capitalization information from CRSP. The final sample consists of 14,381 firm-year observations in the intersection of data from I/B/E/S, Compustat, and CRSP.

[7] The sample period begins in 1990 instead of 1983 (when I/B/E/S began collecting analyst data) because some of the analyst signals, e.g. experience and prior forecasting accuracy percentage, are not meaningful without a prior history to measure them.

5. EMPIRICAL RESULTS

5.1 Analysts' Prediction Performance and Abnormal Returns

First, I document analysts' performance at predicting the forthcoming directional changes in earnings and the abnormal returns associated with these predictions. Table 1, Panel A reports that analysts correctly predict the sign of the change in earnings 76.8 percent of the time. The analysts' percentage of correct predictions improves upon the proportional chance criterion benchmark percentage of 52.5 percent, which indicates that analysts perform better than chance.[8] Table 1, Panel A further examines analysts' performance by reporting percentages of correct predictions within sign-based samples. Analysts perform much better when predicting an earnings decrease (89.5 percent correct) than an earnings increase (73.6 percent correct). Table1, Panel A also reports that analysts predict an annual earnings increase for 80.2 percent of the firm-year observations while only 61.1 percent of the firm-year observations actually experience an annual increase in earnings, which is evidence of an optimistic bias in analysts' prediction of the forthcoming directional earnings change.

Table 1 also provides data on the abnormal returns associated with firms for which analysts predict an earnings increase or decrease. The firms for which analysts predict one-year-ahead earnings will increase (decrease) earn average abnormal returns of 2.3 (1.3) percent. This suggests that a trading strategy taking long (short) positions in firms for which analysts predict an earnings increase (decrease) would not generate substantial abnormal returns. The zero abnormal return suggests that on average share prices reflect the content of analysts' forecasts assuming such forecasts are correct and no returns accrue to a simple strategy based on the sign of earnings change forecasts.

A rather striking feature of this aggregate zero abnormal return arises when I segregate the abnormal returns based on *ex post* knowledge of whether the consensus forecast has the correct sign.

[8] The proportional chance criterion is based on the actual occurrence of earnings increases and decreases and should be used when group sizes are unequal and the researcher wishes to correctly identify members of two (or more) groups (Hair et al, 1998, p. 269). Hair et al (1998, p. 269) suggest classification accuracy should be at least one-fourth greater than that the proportional chance criterion to be considered significant.

Table 1, Panel A reports that when analysts *correctly* predict an earnings increase (decrease), firms earn abnormal returns of 12.2 (-3.2) percent. On the other hand, when analysts *incorrectly* forecast an earnings increase (decrease), the firms earn abnormal returns of -24.7 (37.8) percent. These abnormal returns suggest that an *ex ante* identification of firms for which analysts are correct or incorrect about the sign of the future earnings change has the potential to be rewarding, especially for those of incorrect signs. This paper attempts to capture these abnormal returns by developing two scoring mechanisms to condition the consensus analysts' forecasts of the forthcoming directional earnings change.

Table 1, Panel B reports descriptive statistics on the percentage of correct predictions and the abnormal returns related to the magnitude of the predicted change. As noted earlier, I split the sign-based samples into groups based on the magnitude of the predicted change because I expect the percentage of correctly predicted sign changes in one-year-ahead earnings to increase as the absolute magnitude of the predicted change becomes larger. The data in Panel B confirms that, as expected, the analysts' percentage of correct predictions increases as the absolute magnitude of the predicted change increases. Analysts correctly predict an increase in only 66.2 percent of the firm-year observations in the lowest tercile of predicted change magnitude, but the percentage of correct predictions rises to 80.0 percent in highest tercile. On the other hand, analysts correctly predict a decrease in 79.5 percent of the firm-year observations in the lowest tercile and the percentage rises to 97.2 percent in the highest tercile. I use the percentage of correct predictions from the tercile groups as benchmarks for the portfolios of forecasts identified as more or less likely correct by the conditioning sequence.

Table 1, Panel B also provides descriptive statistics on the average abnormal returns associated with firms sorted terciles based on the magnitude of predicted earnings changes. Regardless of whether or not the forecast is correct, firms with predicted earnings increases in the lowest tercile earn average abnormal returns of 15.1 percent while firms in the highest tercile earn average abnormal returns of -6.9 percent. For firms predicted to experience an earnings decline in the next year, the average abnormal returns decrease from 7.7 percent in the lowest tercile of predicted change to -2.4 percent in the highest tercile.

An examination of the average abnormal returns that accumulate with *ex post* knowledge of whether the forecast correctly predicted the change in earnings reveals where the conditioning sequence has the most potential to capture the abnormal returns documented in Panel A. When analysts *correctly* forecast an increase in annual earnings, the average abnormal return is 31.6 in the lowest tercile, decreasing to -0.4 percent in the highest tercile for increases, while the firms for which analysts *correctly* predict an earnings decrease experience average abnormal returns of 0.0 percent in the lowest tercile and -3.6 percent in the highest tercile. When analysts *incorrectly* forecast the sign of the change in earnings, the market appears to be surprised. For example, the firms for which analysts *incorrectly* predict earnings increases experience average abnormal returns of -17.0 percent in the lowest tercile decreasing further to -32.7 percent in the highest tercile. Thus, the market considerably reduces the value it places on these firms as it realizes they are not experiencing the predicted earnings increase. For the firms for which the analysts predict earnings decreases but actually realize earnings increases, the average abnormal returns are 38.5 percent in the lowest tercile and 34.8 percent in the highest tercile. These results suggest that the potential to generate significant abnormal returns exists in the lowest tercile of correct predicted magnitude increases and the *incorrect* forecasts in all terciles.

Overall the results in Table 1 indicate that analysts make frequent forecast errors with respect to their prediction of the sign of the change in one-year-ahead earnings and significant abnormal returns accumulate to firms with directionally correct or incorrect consensus forecasts.

5.2 Scoring Mechanisms

Table 2 presents descriptive evidence on the analyst score, the fundamental score, and the variables I use to construct them. Panel A provides distributional statistics on the analyst and firm signals that comprise AS and FS. I present descriptive statistics for the variables comprising AS prior to performing the percentile ranking procedure used to compute AS. The distributional statistics in Panel A indicate the sample data used to construct AS contain significant variation in experience, ability, resources, and information environment.

I construct the fundamental score as an aggregation of six fundamental signals. I assign points to firm-year observations based on the quintile ranking of six fundamental signals so the 20th and 80th percentiles represent the average cutoff points for the scoring of the firm-year observations. The statistics in Panel A indicate the sample data used to construct FS contain significant variation between firm-year observations in the 20th and 80th percentiles (the top and bottom quintiles).

Table 2, Panel B contains the univariate correlations between each of the analyst forecast signals, AS, and CORRECT. I find that five of the eight analyst forecast signals correlate in the predicted direction with CORRECT in either the Spearman or Pearson correlations. EXPER, HFAP, and DISP do not relate to CORRECT in the univariate setting. The positive correlation between CORRECT and AS indicates that AS will likely distinguish forecasts on their likelihood of correctly predicting the forthcoming directional earnings change.

Table 2, Panel C contains a correlation table for the fundamental signals, FS, and CHANGE, an indicator variable that equals one if the sign of the one-year-ahead earnings change is positive and zero otherwise. The variables that comprise FS are significantly correlated with the direction of the future change in earnings although the RNOA score has the opposite sign. I also find that FS exhibits a positive correlation with CHANGE, which indicates that as FS increases the likelihood of a firm experiencing an increase in earnings next year increases.[9] Thus, the positive correlation indicates that FS will likely distinguish firms based on their likelihood of experiencing an earnings increase or decrease in the next year.

To construct AS, I estimate pooled logistic regressions using rolling periods of up to five prior years prior to each forecast year. I apply each of these coefficient estimates to forecast year characteristics to get an *ex ante* measure of the likelihood of analyst forecast errors. Table 3 provides descriptive data on the model fit and coefficient estimates. The estimation models exhibit pseudo-R2's ranging from 4.7

[9] To further assess the reasonableness of the fundamental signals, I estimate a logit regression using CHANGE as the dependent variable and the scored variables as the independent variables. They each have the predicted relationship with CHANGE with the exception of RNOA which has a negative relationship, similar to the univariate findings.

percent in 1993 to 11.5 percent in 1990. The likelihood ratios for each of the rolling periods indicate the model is consistently significant each year. Contrary to my expectations, HFAP does not display significance in any of the models.

5.3 Analyst Score and Fundamental Score Performance

Before using AS and FS together in the conditioning sequence, I separately examine each model's ability to distinguish forecasts based on the likelihood of correctly predicting the directional earnings change. To examine each score separately, I rank the firm-year observations independently on AS and FS and place them into terciles and quintiles, respectively. If AS and FS effectively identify the forecasts that are more or less likely to correctly predict the sign of the change in one-year-ahead earnings, then I would expect to find the percentages of correct predictions in the highest (lowest) tercile/quintile to be greater (less) than the unconditioned portfolios' percentages of correct predictions. I also expect the highest tercile/quintile to exhibit greater percentages of correct predictions than the lowest tercile/quintile.

Table 4, Panel A reports the findings related to the AS model. Among firms predicted to experience earnings increases (large, medium, or small), the tercile 3 portfolios (most likely correct) exhibit significantly higher percentages of correct predictions than the respective benchmark (unconditioned) portfolios. For example, tercile 3 of the small predicted increase group is correct 81.7 percent of the time, an improvement of 15.5 percent over the benchmark portfolio. Importantly, tercile 3 portfolios exhibit higher percentages of correct predictions than tercile 1 portfolios in each of the predicted magnitude groups, which should help the conditioning sequence distinguish the forecasts that are more or less likely to be correct.

For predicted decreases, the AS scoring mechanism does not perform well. In Panel A among firms predicted to experience earnings decreases (large, medium, or small), the tercile 3 portfolios (most likely correct) do not exhibit significantly higher percentages of correct predictions than the benchmark (unconditioned) portfolios. The tercile 3 portfolios (more likely correct) also do not have significantly greater percentages of correct predictions than the tercile 1 portfolios (less likely correct). The results related to predicted decreases are not as surprising given the benchmark accuracy for forecasts of medium and large decreases. Overall, AS effectively distinguishes forecasts based on their likelihood of correctly predicting an earnings increase but not an earnings decrease.

Table 4, Panel B reports the findings related to the FS model's ability across quintiles.[10] For predicted increases, the top FS quintile in the large and small magnitude groups exhibit significantly greater percentages of correct predictions than their respective benchmark prediction percentages. Each of the bottom FS quintiles in the magnitude groups within the sample of predicted increases exhibits a significantly lower percentage of correct predictions than its respective benchmark percentages. For predicted decreases in the small and medium magnitude groups the top FS quintile effectively identifies those firms that are less likely to experience an earnings decrease, as indicated by those portfolios' percentages of correct predictions being less than their respective benchmarks. The bottom FS quintile identifies those firm-year observations in the small and medium magnitude groups that are more likely to experience the predicted earnings decrease, as indicated by the portfolios' percentages of correct predictions being greater than respective benchmarks. FS does not effectively distinguish forecast accuracy in the portfolio of large magnitude predicted decreases. Panel B also reveals a significant difference between the percentages of correct predictions of firm-year observations in the top and bottom quintile of FS within each of the sign and magnitude groups. This means FS should help the conditioning sequence split the forecast groups into forecasts that are more or less likely to correctly predict the forthcoming directional earnings change.

5.4 Conditioning Sequence Performance

5.4.1. Prediction Performance

I now examine the percentages of correct predictions for the portfolios identified by the conditioning sequence. Recall, after splitting the sample into predicted sign and magnitude groups, I use the AS and FS scores in a conditioning sequence to identify portfolios of firm-year observations that are more or less likely to correctly predict the directional earnings change. I place firm-year observations that

[10] Due to the discrete nature of FS, the quintiles are not of equal size.

the conditioning sequence identifies as *more* likely to correctly predict an earnings increase (decrease) in portfolios L1, M1, and S1 (portfolios L8, M8, and S8). I place firm-year observations that the conditioning sequence identifies as *less* likely to correctly predict an earnings increase (decrease) in portfolios L4, M4, and S4 (portfolios L5, M5, and S5).

Table 5 reports the conditioning sequence's prediction performance findings and Figure 2 illustrates the results. First I examine whether portfolios of forecasts identified as *more* likely correct have percentages of correct predictions that are greater than their respective benchmark percentages. For predicted increases, portfolios L1, M1, and S1 exhibit percentages of correct predictions (87.6, 85.5, 84.9), representing statistically significant improvements of 7.6, 10.8, and 18.7 percent, respectively, over the benchmark percentages of correct predictions (80.0, 74.7, 66.2). This indicates that the information in AS and FS could enable forecast users to *ex ante* identify a set of firms for which the consensus forecast is more likely to correctly predict the increase in earnings. For the L8 and M8 portfolios, all firm-year observations experience the predicted decrease (100 percent correct predictions) although the improvement over the benchmark is only significant for the M8 portfolio. The improvement of 1.6 percent in the S8 portfolio is not statistically significant. So the conditioning sequence effectively identifies those forecasts that are more likely to correctly predict a decrease of a medium magnitude. Overall, the results suggest the information used in the conditioning sequence identifies the firm-year observations associated with forecasts that are *more* likely to have the correct sign.

I next examine the portfolios of forecasts identified by the conditioning sequence as *less* likely correct to determine whether their percentages of correct predictions are lower than their respective benchmark percentages of correct predictions. For predicted increases (portfolios L4, M4, and S4), I find correct prediction percentages (65.9, 56.8, and 46.2), which are statistically significantly lower than their respective benchmarks (80.0, 74.7, and 66.2). The lower prediction percentages indicate that a user of consensus forecasts could use the conditioning sequence to identify those forecasts that are less likely to correctly predict an increase in earnings. For portfolios M5 and S5 (predicted decreases), I find percentages of correct predictions (86.3 and 64.9), which are statistically significantly lower than the respective benchmarks (91.8 and 79.5). The percentage of correct predictions for portfolio L5 (100) is not significantly less than its benchmark (97.2). Thus, the conditioning sequence effectively identifies the firm-year observations for which the consensus forecast is less likely to correctly predict the change in one-year-ahead earnings.

The last column in Panel A also reports the overall ability of the conditioning sequence to separate the firm-year observations for which the forecasts are more likely correct from the firm-year observations for which the forecasts are less likely correct within magnitude groups. For predicted increases, I find the differences in percentages of correct predictions between the more likely correct portfolios and the less likely correct portfolios are all positive and statistically significant. For predicted decreases, I find the difference is positive and statistically significant for the medium and small magnitude groups. This indicates that the conditioning sequence can take a group of forecasts, condition them on information publicly available, and separate the firm-year observations that are more likely to experience the predicted sign of the change in one-year-ahead earnings from those that are less likely.

5.4.2. Economic significance

The preceding analysis established that the conditioning sequence successfully separates firms *ex ante* based on the likelihood that the consensus forecast correctly predicts the directional change in forthcoming annual earnings. In the following analysis, I assess whether the conditioning sequence's predictions generate economically significant abnormal returns by implementing trading strategies. If share prices are fully efficient with respect to the simple signals used in the conditioning sequence, then it should not be associated with abnormal returns.

Table 6 reports the findings from implementing trading strategies based on the conditioning sequence's identification of more and less likely correct forecasts. As noted before, I also examine the abnormal returns generated by two benchmark strategies, one based on perfect foresight of future changes in earnings and one based on analysts' predictions. The perfect foresight trading strategy takes long (short) positions in those firms that *ex post* experience earnings increases (decreases) and generates an average abnormal portfolio return of 28.7 percent. The analyst forecast strategy takes long (short) positions in firms for which analysts predict earnings increases (decreases) one-year-ahead and generates an average abnormal portfolio return of 1.0 percent. The insignificant abnormal return indicates that the market incorporates the information in consensus analysts' forecasts.

The trading strategy that invests in firms for which the conditioning sequence identifies their forecasts as *more* likely correct, the strong strategy, earns a positive abnormal return in eleven of twelve years, and earns an average abnormal return of 5.4 percent; however, this average abnormal return is not statistically significant. The strong strategy's abnormal returns results are consistent with the *ex post* returns evidence in Table 1, Panel B, which suggests that identifying correct forecasts generates relatively small abnormal returns. Further, the strong strategy takes investment positions in firms for which the actual earnings changes confirm analysts' predictions and are not likely to surprise the market

The trading strategy that invests in the shares of firms identified by the conditioning sequence to be associated with forecasts that are *less* likely correct, the contrarian strategy, generates an average abnormal return of 30.1 percent and the abnormal returns are positive in nine of twelve years. Notice this average abnormal return is as large as the average abnormal return to perfect foreknowledge of the sign of the firm's future earnings change; however, the contrarian strategy is based on *ex ante* predictions for a much smaller set of firm-years. The positive abnormal return to the contrarian strategy indicates that the market is surprised by the sign of the actual earnings change for the firms in these portfolios, on average, and that an investor could use the conditioning sequence to capture some of the abnormal returns by identifying the firms that are more likely to be associated with incorrect forecasts.

I further investigate the economic significance of the conditioning sequence's predictions by examining the average abnormal returns generated by portfolios of firms for which the conditioning sequence identified the directional earnings change prediction as more and less likely correct. Table 7 reports the average abnormal returns generated by each of the portfolios. For predicted increases, the more (less) likely correct portfolios generate positive (negative) average abnormal returns (6.5, -6.9) that are statistically different from zero; however, only the less likely correct portfolio generates average abnormal returns that are statistically significantly different from its benchmark abnormal return (2.3).

This is not surprising because I expect market prices to incorporate consensus analysts' forecasts, which means only the portfolio that surprises the market (less likely correct portfolio) should generate an abnormal return that is different from the unconditioned portfolio's abnormal returns. The table also provides evidence that the conditioning sequence effectively distinguishes the predicted increase firms on the basis of future abnormal returns. The more likely correct portfolio generates average abnormal returns that are greater than the less likely correct portfolio. This indicates that a user of consensus analysts' forecasts could apply the conditioning sequence to firms predicted to experience earnings increases and limit their exposure to taking long positions in firms that will surprise the market with earnings decreases.

On the predicted decrease side, the more and less likely correct portfolios earn average abnormal returns (1.2 and 23.2) that are not significantly different from zero or their benchmark (1.3). Although the more likely correct portfolio generates lower abnormal returns than the less likely correct portfolio, the difference is not statistically significant. I am not surprised by these abnormal returns results because the conditioning sequence has less opportunity and exhibits less ability to distinguish predicted decreases as less likely correct. I also expect the market to fully incorporate consensus analysts' predictions of earnings decreases because of the negative implications of analysts issuing incorrect forecasts.

Figure 3 further illustrates the results in Table 7 by tracing the monthly cumulation of average abnormal returns for each of the portfolios over the twelve month holding period. To provide a benchmark, I also trace the cumulation of abnormal returns for portfolios based on *ex post* knowledge of the actual sign of the change in one-year-ahead earnings, similar to the graph first provided in Ball and Brown (1968).[11] It is interesting to notice the paths of the portfolios in relation to the perfect foresight portfolios. The portfolio of predicted decrease forecasts identified as less likely correct takes a path that rises above the path of the actual earnings increase portfolio. I expect this to occur if the conditioning sequence identifies predicted decrease firms that are likely incorrect, and which surprise the market with earnings increases. The portfolio of earnings increases identified as more likely correct takes a path that

[11] Nichols and Wahlen (2004) replicate the findings of Ball and Brown (1968) using a later time period and show the difference in returns widens between firms that actually realize earnings increases and decreases.

parallels, while remaining below, the path of the portfolio of actual earnings increases. I expect this to occur if the conditioning sequence identifies forecasts that do not surprise the market. The graph also highlights the conditioning sequence's ability to distinguish predicted increase/decrease firms on the basis of future returns. For predicted increases, the portfolio identified as more (less) likely correct takes a path that rises (declines). On the predicted decrease side, the portfolio the portfolio identified as more (less) likely correct takes a path that declines (rises).

5.4.3. Supplemental Tests

In this section, I perform an additional analysis to examine whether the abnormal returns generated by the contrarian trading strategy can be explained by omitted variables associated with future returns.[12] I use an approach similar to Beneish and Vargus (2002). I include the following four characteristics in the portfolio returns regression: (1) the market-to-book ratio (MTB), computed as the market value of equity divided by the book value of equity; (2) returns in the prior year (RET_{t-1}), computed as each firm's prior year return; (3) earnings yield (EPRATIO), computed as income before extraordinary items divided by market value of equity; and (4) accruals (ACC), computed as operating income after depreciation less cash flow from operations.[13] I mean-adjust all independent variables except HEDGE. As a result, I interpret the slope coefficient on HEDGE as the return to the hedge portfolio after controlling for the effect of the other variables. The average estimated coefficients for the year-by-year contrarian strategy portfolio returns model (t-statistics in parentheses) are:[14]

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[12] I also examine whether the abnormal returns generated by the more and less likely correct portfolios cumulate in the four days surrounding the next four quarterly earnings announcements periods to provide further evidence of mispricing based on the market not efficiently processing and impounding information about the likelihood that the forecasts are correct. I find the percentage of abnormal returns cumulated by the conditioning sequence portfolios during the four four-day windows is greater than that of the unconditioned firms; however, the difference is not statistically significant.

[13] I base the inclusion of the variables in the model on: (1) Fama and French's (1992) conjecture that B/M reflects unknown risk factors related to future expected returns; (2) evidence in Jegadeesh (1990) and Jegadeesh and Titman (1993) that finds short-run returns tend to continue in the subsequent year; (3) evidence in Haugen and Baker (1996) that finds low P/E ratio firms outperform high P/E ratio firms on a risk-adjusted basis; (4) evidence in Sloan (1996) that trading strategies based on taking positions in firms located in the extreme deciles of accruals generate average annual abnormal returns of 10.4 percent.

[14] I estimate the model with 826 firm-year observations due to missing data for the independent variables. I also estimate the model in a pooled cross-sectional regression and obtain similar results.

$$AR_{jt+1} = \underset{(-2.97)}{-0.077} + \underset{(1.84)}{0.308}\ HEDGE_{jt} - \underset{(-0.20)}{0.002}\ MTB_{jt} + \underset{(0.18)}{0.005}\ RET_{jt-1} - \underset{(-1.27)}{0.000}\ EPRATIO_{jt} - \underset{(-0.37)}{0.000}\ ACC_{jt} \qquad (2)$$

The contrarian strategy continues to generate positive average abnormal returns (30.8) which are similar to those reported in Table 6. The inclusion of variables associated with subsequent returns does not diminish the profitability of the contrarian strategy, which suggests that the abnormal returns are not the result of market-to-book, price momentum, earnings yield, or accruals effects. The results further strengthen the argument that the market is not incorporating *ex ante* information that would enable it to identify earnings change forecasts of the incorrect sign.

6. CONCLUSION

In this paper, I demonstrate that users of consensus analysts' earnings forecasts can exploit information in (a) the nature of analysts' historical forecast accuracy and firms' earnings predictability, and (b) fundamental analysis of firms' earnings growth to segregate analysts' consensus forecasts of one-year-ahead earnings changes into those likely to be of the correct and incorrect sign. I also demonstrate the economic significance of this ability. Specifically, I show that (1) investors appear to unconditionally incorporate consensus analysts' predictions of the directional earnings change; (2) a conditioning sequence based on the above information significantly increases (reduces) the probability of relying on consensus analysts' forecasts that correctly (incorrectly) predict the sign of the actual change in earnings; (3) a trading strategy based on identifying analysts' forecasts less likely to correctly predict the direction of the forthcoming annual earnings change generates substantial abnormal returns; and (4) the conditioning sequence distinguishes predicted increase firms on the basis of future abnormal returns.

The results from this study have implications for researchers, investors, and educators. The paper provides a tool for researchers and investors to assess the likelihood that the consensus forecast correctly predicts the sign of the change in one-year-ahead earnings. Those conducting empirical asset pricing model research can use the tools developed in this paper to refine the earnings forecast inputs into their intrinsic value models. The results also suggest that information in the financial statements and information about the analysts and the predictability of the firms' earnings stream can be used to counteract the optimism evident in consensus analysts' predictions of the forthcoming earnings increases. Investors can use those findings to implement trading strategies and capitalize on analysts' forecast errors. The results also suggest that analysts do not efficiently use the information in financial statements when developing their earnings forecasts. Educators can use those findings in financial statements analysis courses to convey the importance of understanding how to use financial statement information. They may also use the tools developed in this paper to provide a check for the reasonableness of one-year-ahead earnings forecasts or projections they develop and encourage discussion of why the firm may or may not generate the projected earnings.

The paper's findings raise issues for future research. Future research relating to empirical asset pricing models can examine how the relationships between price and analysts' earnings projections vary across groups of forecasts that are more or less likely to correctly predict the directional change in earnings. Because significant returns are associated with firms missing the magnitude of analysts' forecasts at the earnings announcement date, future research can develop analyst score and fundamental score models to predict *ex ante* the firms that will meet/miss consensus earnings forecasts. Future research can also use the models developed in this paper to explore whether better analysts use the information in financial statements more efficiently and how the firms they follow affect that relationship. Do more accurate analysts appear better because they are following firms with more predictable earnings streams? Are less accurate analysts following firms for which the financial statements provide less indication of future earnings?

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EXHIBIT 1

Analyst Forecast Signals

Signal	Measure	Information Content
EXPER[a]	Number of years experience forecasting earnings for a particular firm.	Analyst firm-specific ability.
HFAP[a]	Prior forecast accuracy percentage based on one-year-ahead change in earnings.	Analyst general ability.
RES[a]	Decile ranking of the number of analysts working for a brokerage house.	Resources available to the analyst when generating a forecast.
TASK[a]	The number of industries the analyst follows.	Amount of time each analyst can spend developing the forecast.
NUM	Number of analysts in the consensus forecast.	Availability of information about the firm.
DISP	Standard deviation of consensus analyst forecast.	Unpredictability of earnings stream.
VAR	Standard deviation of prior five years change in operating income divided by average standard deviation for the firm's industry.	Unpredictability of earnings stream.
APRED	Absolute value of predicted change in one-year-ahead earnings.	Ability of firm to meet sign of earnings change expectations.

[a] I calculate the consensus forecast firm-year measure by averaging the analyst-specific measures for the analysts in the consensus.

EXHIBIT 2

Fundamental Analysis Signals

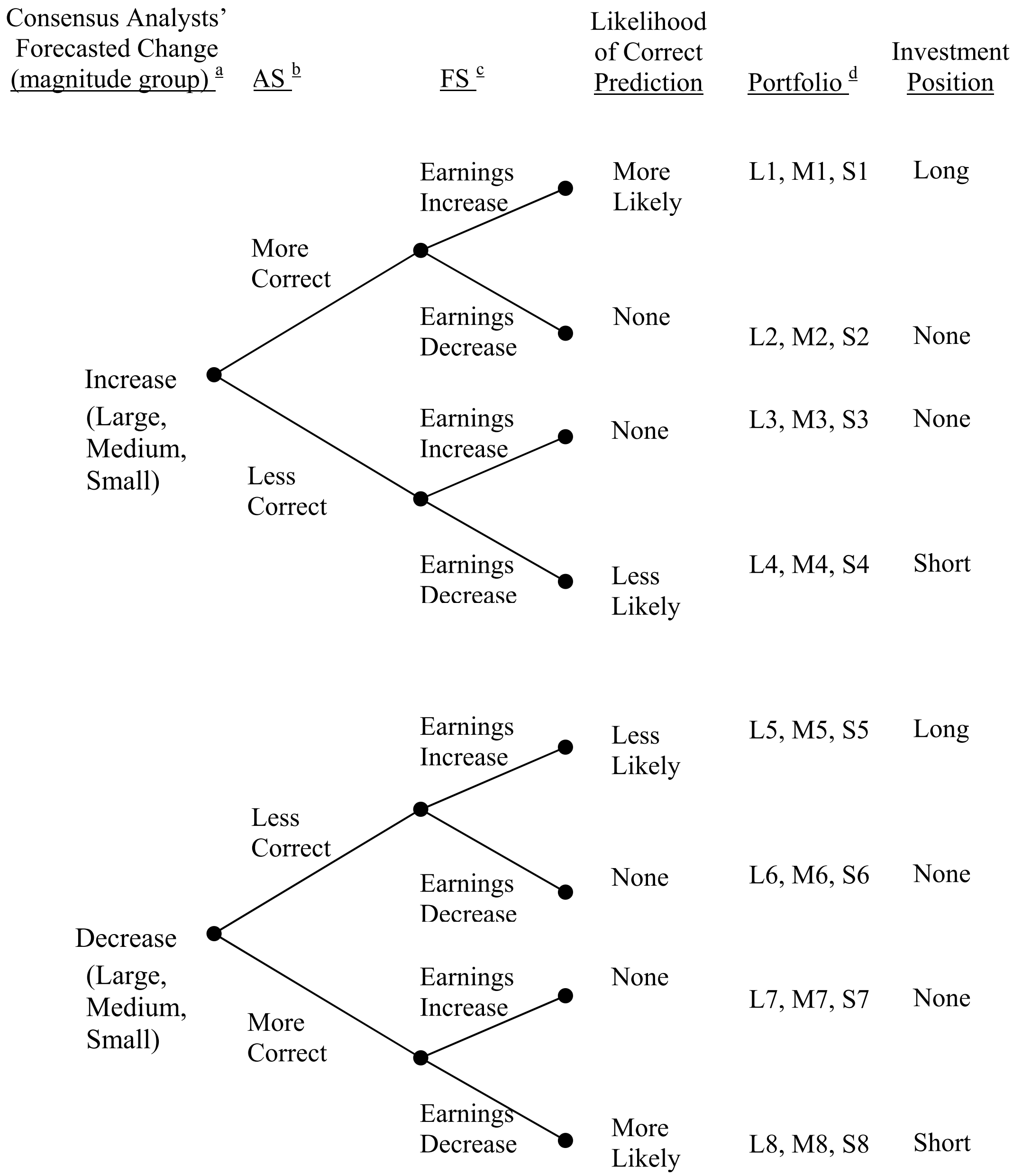
				Quintile Scoring		
Signal	**Measure**	**Information Content**		**+1**	**0**	**-1**
RNOA	Operating Income / AVGNOA $_{t-1}$[a]	Mean reversion in earnings when RNOA is extreme.		Bottom	Middle	Top
GM	ΔGM[b] – ΔSales Where Δ = rate of change.	Firm's changing position in input markets.		Top	Middle	Bottom
SG&A	SGA_t / $Sales_t$ – SGA_{t-1} / $Sales_{t-1}$	Changes in the costs of operations relative to sales.	Revenues Increase	Top	Middle	Bottom
			Revenues Decrease	Top	Middle	Bottom
ATO	$Sales_t/TA_{t-1}$ – $Sales_{t-1}/TA_{t-2}$	Changes in the efficiency of firm operations.		Top	Middle	Bottom
G^{NOA}	(NOA_t - $AVGNOA_{t-1}$) / $AVGNOA_{t-1}$	Current period investments that are expensed at a faster rate than economic reality.	Within RNOA quintiles	Bottom	Middle	Top
ACC	[Operating Income– Cash From Operations] / AVGNOA $_{t-1}$	Persistence of earnings when accruals are high.	Within RNOA quintiles	Bottom	Middle	Top

[a] $AVGNOA_{t-1}$ equals the average net operating assets from the beginning and ending of the prior year. Net operating assets equal Common Equity + Financial Obligations [Debt in Current Liabilities + Total Long-Term Debt + Preferred Stock] – Financial Assets [Cash and Short-Term Investments – Other].

[b] Gross Margin equals Sales less Cost of Goods Sold.

FIGURE 1

Conditioning Consensus Analysts' Earnings Forecasts with AS and FS



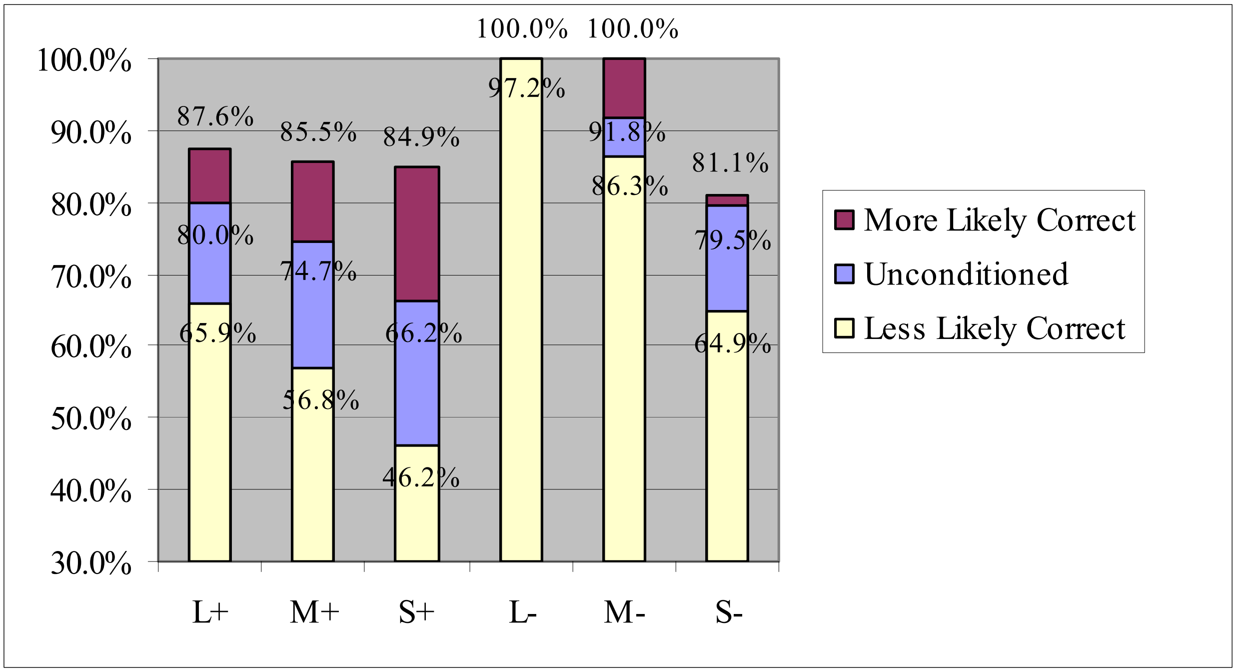
[a] I calculated the sign of the forecasted change in earnings as the first consensus median analysts' forecast from I/B/E/S International after the prior earnings announcement less prior period's earnings. I place forecasts into terciles based on the magnitude of the forecasted change and assign the top (bottom) terciles to the High (Low) group and the middle tercile to the Medium group.

[b] I assign the top (bottom) AS tercile to the More Correct (Less Correct) node because AS suggests the earnings forecast more (less) likely correctly predicts the direction of the forthcoming annual earnings change.

[c] I assign the top (bottom) FS quintile to the Earnings Increase (Earnings Decrease) node because the fundamentals indicate the firm will likely experience an increase (decrease) in earnings.

[d] H (L) signifies high (low) magnitude forecasted change while M signifies a medium magnitude change. The numbers refer to the final nodes in the conditioning sequence.

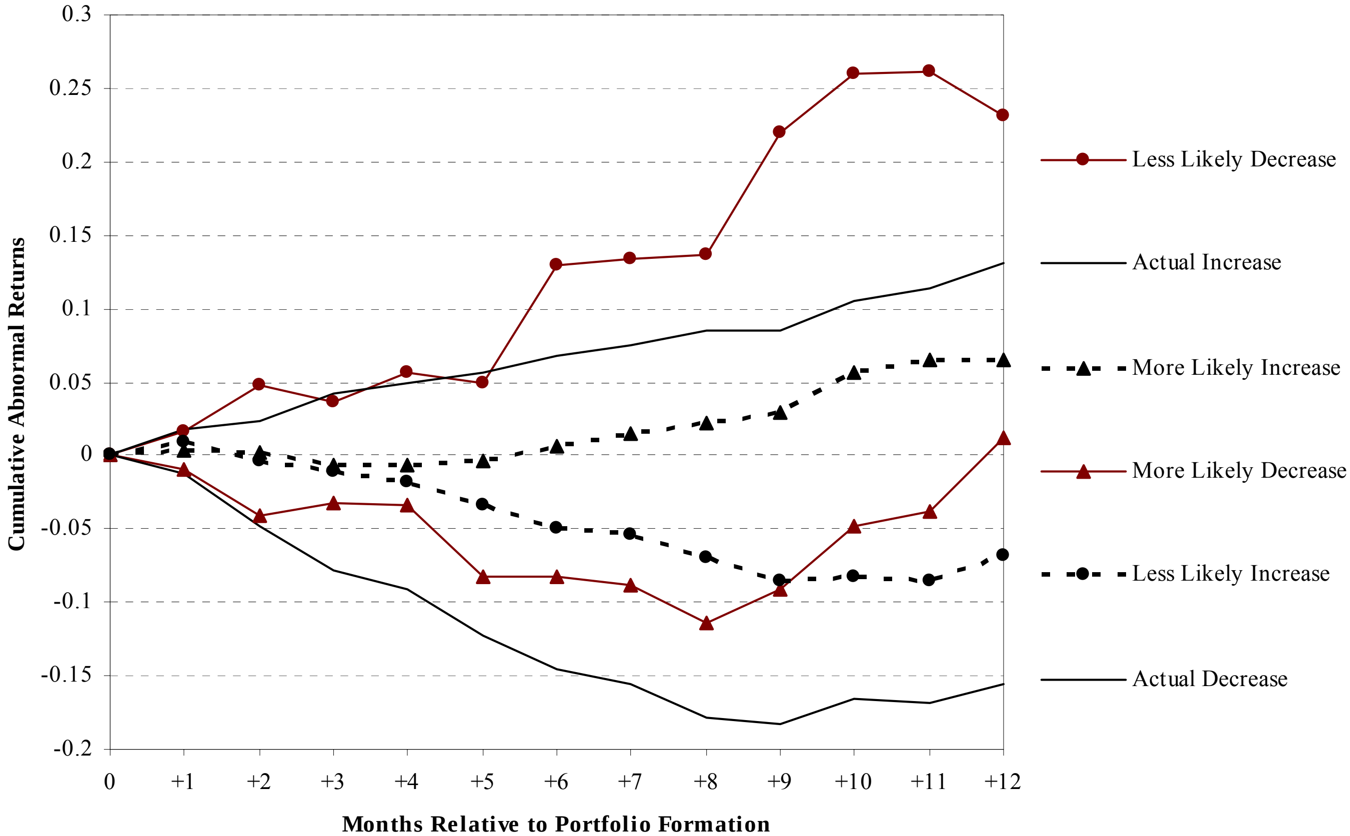
FIGURE 2
The Percentage of Correct Predictions for Unconditioned and Conditioned Consensus Analysts' Forecasts



Notes
L+ indicates the large magnitude group of predicted increases.
M+ indicates the medium magnitude group of predicted increases.
S+ indicates the small magnitude group of predicted increases.
L- indicates the large magnitude group of predicted decreases.
M- indicates the medium magnitude group of predicted decreases.
S- indicates the small magnitude group of predicted decreases.

FIGURE 3

The Association Between Change in Annual Earnings, Likely Change in Annual Earnings, and Cumulative Abnormal Returns



Notes

The Less Likely Decrease portfolio contains the firms placed in portfolios L5, M5, and S5.
The Actual Increase portfolio contains all firms that experience an increase in earnings.
The More Likely Increase portfolio contains the firms placed in portfolios L1, M1, and S1.
The More Likely Decrease portfolio contains the firms placed in portfolios L8, M8, and S8.
The Less Likely Increase portfolio contains the firms placed in portfolios L4, M4, and S4.
The Actual Decrease portfolio contains all firms that experience a decrease in earnings.

TABLE 1
Predicted Earnings Changes, Actual Earnings Changes, and Abnormal Returns for the Period 1991-2002

Panel A: Prediction Performance and Abnormal Returns by Sign

Predicted Change[a]	N (Percentage)	Actual – N (Percentage)	Correct Prediction Percentage[b]	All AR[c]	Correct[d] N	Correct[d] AR	Incorrect N	Incorrect AR
Increase	11,528 (80.2%)	8,789 (61.1%)	73.6%	2.3%	8,489	12.2%	3,039	-24.7%
Decrease	2,853 (19.8%)	5,592 (38.9%)	89.5%	1.3%	2,553	-3.2%	300	37.8%
Total[e]:	14,381	**Overall:**	76.8%					

Panel B: Prediction Performance and Abnormal Returns by Sign and Magnitude Terciles

Predicted Change[a]	Tercile	N	Predicted Change Mean	Correct Prediction Percentage[b]	All AR[c]	Correct[d] N	Correct[d] AR	Incorrect N	Incorrect AR
Increase	Large[f]	3,841	1.625	80.0%	-6.9%	3,074	-0.4%	767	-32.7%
	Medium	3,862	0.200	74.7%	-1.2%	2,884	8.5%	978	-28.9%
	Small	3,825	0.075	66.2%	15.1%	2,531	31.6%	1,294	-17.0%
Decrease	Small	949	-0.059	79.5%	7.7%	754	0.0%	195	38.5%
	Medium	949	-0.252	91.8%	-1.7%	871	-5.4%	78	43.6%
	Large	955	-1.097	97.2%	-2.4%	928	-3.6%	27	34.8%

[a] I calculate the sign of the forecasted change in earnings as the first consensus median analysts' forecast after the prior earnings announcement constructed from the I/B/E/S International Detail file less prior period's earnings.
[b] I present the overall correct prediction percentage calculated as the proportion of forecasts that correctly predict the sign of the change in one-year-ahead earnings to total forecasts for that predicted change. I calculate the sign of the actual change in annual earnings using the difference between current and prior period earnings reported in I/B/E/S.
[c] I report the average yearly returns for each cell based on an equally-weighted holding. I calculate abnormal returns for each of the firm-year observations based on a holding period beginning the first day of the fifth month after the prior fiscal year end and ending the last day of the fourth month after the current fiscal year end. Abnormal returns, AR_{jt} , represent the sum over the holding period of the differences between monthly returns for firm j and returns for CRSP size-based decile, based on the prior year market value of equity.
[d] I determine whether each consensus forecast is correct by comparing the sign of the actual change in earnings to the sign of the analysts' forecasted change.
[e] I remove observations that analysts' predict no change or experience no change.
[f] I label the top (bottom) tercile of predicted change magnitude as the Large (Small) groups and the middle tercile of predicted change magnitude as the Medium group.

TABLE 2
Descriptive Statistics for AS and FS Signals

Panel A: Summary Statistics on the Distribution of Analyst and Fundamental Score Signals
(14,381 Firm-Year Observations between 1991 and 2002)

Variable	Mean	Standard Deviation	P20 [a]	Median	P80 [a]	Min	Max
EXPER	2.732	2.104	1.049	2.000	4.216	0.000	17.000
HFAP	0.661	0.211	0.548	0.708	0.803	0.000	1.000
RES	7.779	1.481	6.894	8.217	8.990	0.000	9.000
TASK	8.998	4.879	5.615	8.000	12.167	1.000	62.000
NUM	4.303	4.616	1.000	3.000	6.125	1.000	43.000
DISP	0.069	1.385	0.000	0.017	0.082	0.000	165.463
VAR	0.735	4.413	0.046	0.138	0.476	0.001	205.889
APRED	0.601	20.182	0.081	0.198	0.450	0.000	1,964.000
AS	1.199	0.607	0.657	1.224	1.706	-1.521	4.045
RNOA	0.018	71.078	0.062	0.201	0.434	-6,947.330	4,726.800
GM	0.001	3.163	-0.075	0.002	0.071	-274.600	93.979
SG&A	-0.014	3.660	-0.017	0.000	0.016	-268.676	298.457
ATO	-0.145	0.974	-0.313	-0.029	0.148	-32.313	24.539
G	1.028	33.858	-0.014	0.229	0.753	-1,297.970	2,035.810
ACC	0.189	26.819	-0.111	0.014	0.173	-598.740	2,364.400
FS	-0.007	1.630	-1.000	0.000	1.000	-6.000	6.000

Panel B: Correlations between Analyst and Firm Characteristics, AS, and CORRECT
(Pearson (Spearman) above (below) the diagonal)

	CORRECT	EXPER	HFAP	RES	TASK	NUM	DISP	VAR	APRED	AS
CORRECT		-0.009	0.006	0.064***	-0.040***	0.072***	0.005	0.000	-0.003	0.215***
EXPER	-0.003		0.231***	0.079***	0.104***	0.176***	0.006	-0.034***	-0.005	0.000
HFAP	0.005	0.189***		0.158***	0.049***	0.090***	0.008	-0.022***	0.005	0.061***
RES	0.056***	0.045***	0.157***		-0.303***	0.167***	0.007	0.001	-0.007	0.248***
TASK	-0.037***	0.138***	0.031***	-0.219***		-0.174***	-0.011	-0.027***	-0.003	-0.182***
NUM	0.081***	0.267***	-0.020**	0.009	-0.130***		0.017**	-0.013	-0.005	0.413***
DISP	0.009	0.224***	-0.045***	-0.031***	-0.047***	0.706***		0.001	0.808***	-0.003
VAR	-0.054***	-0.156***	-0.046***	-0.042***	-0.073***	-0.095***	0.059***		0.001	-0.066***
APRED	0.176***	0.042***	0.038***	0.068***	-0.047***	0.081***	0.237***	0.185***		0.010
AS	0.216***	0.027***	0.053***	0.216***	-0.163***	0.395***	0.020**	-0.317***	0.582***	

***significant at <0.01 ** significant at < 0.05 * significant at < 0.10

Panel C: Correlations between Fundamental Signals, FS, and CHANGE

(Pearson (Spearman) above (below) the diagonal)

	CHANGE	RNOA	GM	SG&A	ATO	G	ACC	FS
CHANGE	***	-0.021 **	0.028 ***	0.038 ***	0.069 ***	0.116 ***	0.042 ***	0.105 ***
RNOA	-0.021 **	***	-0.134 ***	0.029 ***	-0.048 ***	0.003	-0.001	0.330 ***
GM	0.028 ***	-0.134 ***	***	-0.059 ***	0.078 ***	0.058 ***	0.017 **	0.373 ***
SG&A	0.037 ***	0.029 ***	-0.059 ***	***	0.112 ***	-0.012	0.019 **	0.422 ***
ATO	0.069 ***	-0.048 ***	0.078 ***	0.112 ***	***	0.114 ***	-0.018 **	0.481 ***
G	0.116 ***	0.003	0.058 ***	-0.012	0.114 ***	***	0.171 ***	0.516 ***
ACC	0.042 ***	-0.001	0.017 **	0.019 **	-0.018 **	0.171 ***	***	0.460 ***
FS	0.101 ***	0.321 ***	0.360 ***	0.406 ***	0.460 ***	0.506 ***	0.448 ***	***

***significant at <0.01 ** significant at < 0.05 * significant at < 0.10

[a] I report the average 20th and 80th percentile cutoffs for the twelve year period.

Variable Definitions:

CORRECT = 1 if sign of actual change in one-year ahead earnings equals sign of predicted change, 0 otherwise
EXPER = Mean number of years experience forecasting for a particular firm.
HFAP = Mean historical forecast accuracy percentage based on one-year-ahead change in earnings.
RES = Mean decile ranking of the number of analysts working for a brokerage house.
TASK = Mean number of industries the analysts' follow.
NUM = Number of analysts in the consensus forecast.
DISP = Standard deviation of consensus analyst forecast.
VAR = Standard deviation of prior five years change in operating income divided by average standard deviation for the firm's industry.
APRED = Absolute value of predicted change in one-year-ahead earnings.
AS = Estimate of analyst accuracy based on logistic analysis.
CHANGE = 1 if earnings increase in next period, 0 otherwise
RNOA = Operating Income / $AVGNOA_{t-1}$
AVGNOA = Average net operating assets from the beginning and ending of the prior year
NOA = Common Equity + Debt in Current Liabilities + Total Long-Term Debt + Preferred Stock - Cash and Short-Term Investments + Other
GM = Δ [Sales less Cost of Goods Sold] [b] – ΔSales Where Δ = rate of change.
SG&A = SGA_t / $Sales_t$ – SGA_{t-1} / $Sales_{t-1}$
ATO = $Sales_t$ / TA_{t-1} – $Sales_{t-1}$ / TA_{t-2}
G = (NOA_t - $AVGNOA_{t-1}$) / $AVGNOA_{t-1}$
ACC = [Operating Income – Cash From Operations] / $AVGNOA_{t-1}$
FS = Firm specific sum of fundamental signal scores.

TABLE 3
Modeling the Ability of Analysts to Predict the Sign of the Change in One-year-ahead Annual Earnings

$$CORRECT = \alpha + \beta_1 REXPER + \beta_2 RHFAP + \beta_3 RTASK + \beta_4 RRES + \beta_5 RNUM + \beta_6 RDISP + \beta_7 RVAR + \beta_8 RAPRED$$

	Year	REXPER	RHFAP	RTASK	RRES	RNUM	RDISP	RVAR	RAPRED	Pseudo- R^2	Likelihood Ratio	Obs
Predicted Sign [a]		+	+	-	+	+	-	-	+			
Coefficient	1990	-0.009	-0.003	-0.011	-0.001	0.049	-0.031	-0.004	0.014	0.115	13.83	113
Chi-square		*0.90*	*0.09*	*1.52*	*0.01*	*5.15*	*2.39*	*0.20*	*2.59*			
Coefficient	1991	-0.003	0.004	-0.005	-0.004	0.016	-0.009	-0.008	0.018	0.069	54.16	757
Chi-square		*1.19*	*2.22*	*2.64*	*1.91*	*8.90*	*3.32*	*7.55*	*33.27*			
Coefficient	1992	-0.002	0.001	-0.001	0.000	0.016	-0.014	-0.009	0.016	0.051	83.58	1,591
Chi-square		*0.92*	*0.28*	*0.13*	*0.01*	*19.73*	*15.87*	*18.13*	*57.69*			
Coefficient	1993	-0.001	0.000	0.001	0.003	0.017	-0.019	-0.008	0.015	0.047	118.96	2,475
Chi-square		*0.61*	*0.07*	*0.12*	*2.58*	*35.55*	*44.86*	*19.66*	*75.20*			
Coefficient	1994	-0.001	0.000	0.001	0.002	0.018	-0.021	-0.007	0.016	0.051	180.03	3,456
Chi-square		*0.65*	*0.06*	*0.31*	*2.78*	*56.57*	*75.86*	*22.98*	*110.22*			
Coefficient	1995	-0.002	0.001	0.001	0.003	0.018	-0.018	-0.008	0.016	0.051	231.41	4,400
Chi-square		*1.65*	*0.46*	*0.32*	*6.71*	*66.53*	*77.91*	*37.57*	*140.13*			
Coefficient	1996	-0.001	-0.002	0.001	0.005	0.016	-0.017	-0.008	0.015	0.048	248.63	5,022
Chi-square		*0.34*	*1.64*	*0.85*	*14.82*	*64.16*	*80.11*	*39.28*	*141.99*			
Coefficient	1997	-0.001	-0.001	0.000	0.004	0.017	-0.017	-0.008	0.015	0.049	276.59	5,555
Chi-square		*1.21*	*0.55*	*0.01*	*14.06*	*74.58*	*82.45*	*42.87*	*158.00*			
Coefficient	1998	-0.002	-0.001	-0.002	0.003	0.016	-0.015	-0.008	0.015	0.048	305.86	6,264
Chi-square		*3.79*	*0.35*	*3.67*	*6.50*	*81.75*	*75.80*	*56.00*	*172.47*			
Coefficient	1999	-0.003	0.000	-0.002	0.003	0.016	-0.012	-0.009	0.015	0.049	342.16	6,869
Chi-square		*7.17*	*0.21*	*5.26*	*6.07*	*89.86*	*58.83*	*65.76*	*188.56*			
Coefficient	2000	-0.003	-0.001	-0.003	0.002	0.017	-0.012	-0.008	0.016	0.052	391.77	7,304
Chi-square		*7.70*	*0.95*	*8.30*	*4.32*	*110.48*	*67.13*	*53.31*	*225.65*			
Coefficient	2001	-0.005	0.000	-0.002	0.003	0.015	-0.010	-0.006	0.017	0.057	440.69	7,514
Chi-square		*18.52*	*0.07*	*5.84*	*11.81*	*102.94*	*49.40*	*33.20*	*280.89*			
Yearly [b]	All	-0.003	0.000	-0.002	0.003	0.019	-0.016	-0.007	0.016		571.32	12 years
t-statistic		-3.90	-0.09	-1.49	2.72	6.43	-6.40	-7.80	17.94			
Pooled	All	-0.003	0.000	0.015	0.003	-0.001	-0.013	-0.007	0.016	0.051	692.27	13,293
Chi-square		15.61	0.05	176.21	20.73	2.83	127.73	79.02	451.11			

[a] I predict the relation between each variable and CORRECT, which equals one if the sign of the actual change in earnings matches the sign of the analysts' forecasted change, and zero otherwise.
[b] I estimate the logit regression on a yearly basis and report the mean estimated coefficients along with the t-statistics that are calculated as the mean of the estimated coefficients relative to their estimated standard errors.

TABLE 4
Prediction Performance based on Analysts' Forecasts Conditioned by AS and FS for the Period 1991-2002

Panel A: Prediction Performance by AS Terciles

Predicted change	Magnitude group [a]	AS rank [b]	N	N - Correct	Correct Prediction Percentage (CPP) [c]	Benchmark Prediction Percentage (BPP) [d]	CPP - BPP [e]		Tercile 3 – Tercile 1 [f]
Increase	Large	3	1,280	1,099	85.9%		5.9%	***	
		2	1,284	1,028	80.1%	80.0%	0.1%		11.7%***
		1	1,277	947	74.2%		-5.8%	***	
	Medium	3	1,287	1,089	84.6%		9.9%	***	
		2	1,293	955	73.9%	74.7%	-0.8%		19.1%***
		1	1,282	840	65.5%		-9.2%	***	
	Small	3	1,276	1,043	81.7%		15.5%	***	
		2	1,278	860	67.3%	66.2%	1.1%		32.3%***
		1	1,271	628	49.4%		-16.8%	***	
Decrease	Small	3	318	254	79.9%		0.4%		
		2	320	255	79.7%	79.5%	0.2%		1.1%
		1	311	245	78.8%		-0.7%		
	Medium	3	317	295	93.1%		1.3%		
		2	320	293	91.6%	91.8%	-0.2%		2.4%
		1	312	283	90.7%		-1.1%		
	Large	3	318	308	96.9%		-0.3%		
		2	321	315	98.1%	97.2%	0.9%		0.4%
		1	316	305	96.5%		-0.7%		

***significant at <0.01 ** significant at < 0.05 * significant at < 0.10

Panel B: Prediction Performance by FS Quintiles

Predicted change	Magnitude group [a]	FS rank [b]	N	N - Correct	Correct Prediction Percentage (CPP) [c]	Benchmark Prediction Percentage (BPP) [d]	CPP - BPP [e]	Quintile 5 – Quintile 1 [f]
Increase	Large	5	822	702	85.4%		5.4%***	
		4	794	669	84.3%		4.3%***	
		3	1,047	839	80.1%	80.0%	0.1%	16.3%***
		2	648	498	76.9%		-3.1%**	
		1	530	366	69.1%		-10.9%***	
	Medium	5	540	414	76.7%		2.0%	
		4	774	587	75.8%		1.1%	
		3	1,174	905	77.1%	74.7%	2.4%**	10.8%***
		2	790	593	75.1%		0.4%	
		1	584	385	65.9%		-8.8%***	
	Small	5	523	361	69.0%		2.8%*	
		4	712	486	68.3%		2.1%	
		3	1,110	744	67.0%	66.2%	0.8%	6.9%***
		2	831	537	64.6%		-1.6%	
		1	649	403	62.1%		-4.1%**	
Decrease	Small	5	146	106	72.6%		-6.9%**	
		4	189	139	73.5%		-6.0%**	
		3	245	193	78.8%	79.5%	-0.7%	-14.2%*
		2	172	145	84.3%		4.8%*	
		1	197	171	86.8%		7.3%***	
	Medium	5	148	127	85.8%		-6.0%***	
		4	191	174	91.1%		-0.7%	
		3	239	218	91.2%	91.8%	-0.6%	-11.6%***
		2	175	161	92.0%		0.2%	
		1	196	191	97.4%		5.6%***	
	Large	5	166	160	96.4%		-0.8%	
		4	183	176	96.2%		-1.0%	
		3	234	228	97.4%	97.2%	0.2%	-2.1% ***
		2	167	162	97.0%		-0.2%	
		1	205	202	98.5%		1.3%	

***significant at <0.01 ** significant at < 0.05 * significant at < 0.10

[a] Large (Small) groups consist of forecasts in the largest (smallest) tercile of magnitude forecasted change while Medium groups consist of forecasts in the middle tercile of magnitude forecasted change.
[b] I rank firm-year observations based on AS (FS) and place them into terciles (quintiles). Tercile/quintile 1 (3/5) contains the lowest (highest) values.
[c] I calculate correct prediction percentages as the number of forecasts that correctly predict the sign of the change in one-year-ahead earnings divided by the total forecasts for that predicted change. I calculate the sign of the actual change in annual earnings as the difference between current and prior period earnings reported in I/B/E/S.
[d] I report benchmark correct prediction percentage as the unconditioned correct prediction percentage for the Large, Medium and Small magnitude groups, as reported in Table 1, Panel B.
[e] I determine the statistical significance of the difference using z-statistic tests.
[f] This column calculates the difference between the portfolio of more likely correct forecasts and the portfolio of less likely correct forecasts for each magnitude group. I determine the statistical significance of the difference using z-statistic tests.

TABLE 5

Prediction Performance of the Conditioned Analysts' Forecasts for the Period 1991-2002

Portfolio [a]	Correct Likelihood Assessment	N	N Correct	Correct Prediction Percentage (CPP) [b]	Benchmark Prediction Percentage (BPP) [c]	CPP - BPP [d]	Portfolio 1(8) – Portfolio 4(5) [e]
L1	More Likely Correct	209	183	87.6%	80.0%	7.6%***	21.7**
M1	More Likely Correct	256	219	85.5%	74.7%	10.8%***	28.7**
S1	More Likely Correct	279	237	84.9%	66.2%	18.7%***	38.7**
L2	None	216	179	82.9%	80.0%	2.9%	
M2	None	204	163	79.9%	74.7%	5.2%	
S2	None	194	154	79.4%	66.2%	13.2%***	
L3	None	252	199	79.0%	80.0%	-1.0%	
M3	None	264	187	70.8%	74.7%	-3.9%	
S3	None	245	148	60.4%	66.2%	-5.8%	
L4	Less Likely Correct	255	168	65.9%	80.0%	-14.1%***	
M4	Less Likely Correct	206	117	56.8%	74.7%	-17.9%***	
S4	Less Likely Correct	221	102	46.2%	66.2%	-20.0%***	
L5	Less Likely Correct	52	52	100.0%	97.2%	2.8%	
M5	Less Likely Correct	73	63	86.3%	91.8%	-5.5%**	
S5	Less Likely Correct	57	37	64.9%	79.5%	-14.6%***	
L6	None	52	51	98.1%	97.2%	0.9%	
M6	None	46	46	100.0%	91.8%	8.2%**	
S6	None	54	45	83.3%	79.5%	3.8%	
L7	None	52	49	94.2%	97.2%	-3.0%	
M7	None	50	43	86.0%	91.8%	-5.8%*	
S7	None	57	47	82.5%	79.5%	3.0%	
L8	More Likely Correct	48	48	100.0%	97.2%	2.8%	0.0
M8	More Likely Correct	48	48	100.0%	91.8%	8.2%**	13.7**
S8	More Likely Correct	53	43	81.1%	79.5%	1.6%	16.2**

***significant at <0.01 ** significant at < 0.05 * significant at < 0.10

[a] Figure 1 illustrates the portfolio assignments. L (S) signifies large (small) magnitude forecasted change while M signifies a medium magnitude change. The numbers refer to nodes in the conditioning sequence. 1 and 8 (4 and 5) identify forecasts that are more (less likely) to correctly predict the direction of the future earnings change.
[b] I calculate correct prediction percentages as the number of forecasts that correctly predict the sign of the change in one-year-ahead earnings divided by the total forecasts for that predicted change. I calculate the sign of the actual change in annual earnings as the difference between current and prior period earnings reported in I/B/E/S.
[c] I report benchmark correct prediction percentage as the unconditioned correct prediction percentage for the Large, Medium and Small magnitude groups, as reported in Table 1, Panel B.
[d] I determine the statistical significance of the difference using z-statistic tests.
[e] This column calculates the difference between the portfolio of more likely correct forecasts and the portfolio of less likely correct forecasts for each magnitude group. I determine the statistical significance of the difference using z-statistic tests.

TABLE 6

Trading Strategy Returns Based on the Conditioned Analysts' Forecasts for the Period 1991-2002

$$AR_{jt+1} = b_0 + b_1 HEDGE_{jt} + e_{jt}$$

	Position	Portfolios[a]	N	Portfolio Abnormal Return[b]	R^2	N-years positive returns
Strategies						
Perfect foresight	Long	Actual Increase	14,381	28.7%***	0.0577	12
	Short	Actual Decrease				
Analyst Forecast	Long	Predicted Increase	14,381	1.0%	0.0030	7
	Short	Predicted Decrease				
Strong	Long	L1,M1,S1	893	5.4%	0.0094	11
	Short	L8,M8,S8				
Contrarian	Long	L5,M5,S5	864	30.1%**	0.0368	9
	Short	L4,M4,S4				

***significant at <0.01 ** significant at < 0.05 * significant at < 0.10

[a] I use L, M, and S to denote Large, Medium, and Small magnitude predicted change. The numbers refer to nodes in the conditioning sequence. 1 and 8 (4 and 5) identify forecasts that are more (less likely) to correctly predict the direction of the future earnings change.

[b] I calculate abnormal returns, AR_{jt} , as the sum over the holding period of the differences between monthly returns for firm j and returns for CRSP size-based decile, based on the prior year market value of equity. Implied portfolio abnormal returns are equal to b_1 in the regression. I determine significance by calculating t-statistics based on the mean of the estimated coefficients relative to their estimated standard errors.

TABLE 7

Abnormal Returns Based on the Conditioned Analysts' Forecasts for the Period 1991-2002

Correct Likelihood Assessment	Portfolios [a]	N	Portfolio Abnormal Return (AR) [b]	Benchmark Abnormal Return (BAR) [c]	AR – BAR	More Likely Correct – Less Likely Correct
More Likely Correct Increase	L1,M1,S1	744	6.5%**	2.3%	4.2%	13.4%***
Less Likely Correct Increase	L4,M4,S4	682	-6.9%**	2.3%	-9.2%***	
Less Likely Correct Decrease	L5,M5,S5	182	23.2	1.3%	21.9%	
More Likely Correct Decrease	L8,M8,S8	149	1.2	1.3%	-0.1%	-22.0%

***significant at <0.01 ** significant at < 0.05 * significant at < 0.10

[a] I use L, M, and S to denote Large, Medium, and Small magnitude predicted change. The numbers refer to nodes in the conditioning sequence. 1 and 8 (4 and 5) identify forecasts that are more (less likely) to correctly predict the direction of the future earnings change.

[b] I calculate abnormal returns, AR_{jt} , as the sum over the holding period of the differences between monthly returns for firm j and returns for CRSP size-based decile, based on the prior year market value of equity. Implied portfolio abnormal returns are equal to b_1 in the regression. I determine significance by calculating t-statistics based on the mean of the estimated coefficients relative to their estimated standard errors.

[c] I report benchmark abnormal returns as the unconditioned abnormal returns for the respective predicted sign, as reported in Table 1, Panel A.