The information content of analyst stock recommendations

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Comments welcomed

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Abstract

We investigate the relation between analyst stock recommendations and eight concurrently available variables that have predictive power for stock returns. We find that analysts generally pay little attention to the large sample predictive attributes of these variables. In seven out of eight cases, analysts' stock recommendations are directionally opposite to the variable's normative usage in returns prediction. In general, analysts exhibit a strong bias in favor of glamour stocks with growth characteristics.

Despite this general bias, analyst recommendations have incremental predictive power for future returns. In fact, after controlling for the other predictive variables, the predictive power of the *level* of the analyst recommendation increases. These findings suggest that analyst stock recommendations contain information that is largely orthogonal to the information in the other predictive variables. We discuss the implications of these results for analysts, and for investors who rely on their recommendations.

1. Introduction

Researchers and practitioners have long been interested in understanding how the activities of financial analysts affect capital market efficiency. Currently in the United States, over 3,000 analysts work for more than 350 sell-side investment firms.[1] These analysts produce corporate earnings forecasts, write reports on individual companies, provide industry and sector analyses, and issue stock recommendations. Most prior studies have concluded that the information they produce promotes market efficiency by helping investors to value companies' assets more accurately.[2]

This study examines the information content of analyst stock recommendations. A stock recommendation represents an analyst's professional judgment on the expected price appreciation (or depreciation) of a given stock in the near future. As Elton, Gruber, and Grossman (1986, page 699) observed, these recommendations represent "one of the few cases in evaluating information content where the forecaster is recommending a clear and unequivocal course of action rather than producing an estimate of a number, the interpretation of which is up to the user." In short, these recommendations offer a rare opportunity to study analyst preferences across stocks at a given point in time.

Our study critically evaluates the investment value of analyst stock recommendations. Specifically, we analyze the relation between analysts' stock recommendations and other concurrently available variables that also have predictive power for stock returns. Prior studies show analyst recommendations affect stock prices and trading volume at the time of their release, and that they have some ability to predict future returns.[3] However, little is known about the decision process that underpins these recommendations. We provide

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[1] See www.bulldogresearch.com. These statistics do not include "Associates" and other junior analysts that provide research support.

[2] See reviews of this literature, see Schipper (1991) and Brown (2000).

[3] Stickel (1995) examines the immediate market impact of stock recommendations. Elton, Gruber, and Grossman (1986), Womack (1996), and Barber, Lehavy, McNichols, and Trueman (2000) show firms that receive more favorable (less favorable) recommendations subsequently earn higher (lower) returns.

evidence on the type of firm preferred by analysts, and whether these preferences are warranted in light of future returns.

Our study is motivated by three main objectives. First, we document the preferences of sell-side analysts by providing a *descriptive* profile of firms that receive stronger recommendations, as well as firms that analysts tend to upgrade (downgrade). Second, we compare the return prediction performance of the analysts to the performance of other predictive variables gleaned from the academic literature. Our goal in this analysis is more *prescriptive* in nature. To the extent that analysts do not fully incorporate large sample predictive patterns in expected returns, we aim to develop a decision aid that will assist their efforts. Finally, we critically evaluate the usefulness of analyst recommendations in returns prediction after controlling for other predictive variables. In this third stage, our goal is to assist buy-side market participants in evaluating the role and relevance of analyst recommendations in their investment decisions. Specifically, we are interested in whether fundamental analysts can be helpful to quantitative investors, and if so, for what types of firms.

Our investigation proceeds in two parts. In the first part, we document key characteristics of firms preferred by sell-side analysts. This part of our study is similar in spirit to recent studies by Finger and Landsman (1999) and Stickel (1999). However, given our interest in the role of analyst recommendations in investment decisions, our focus is on explanatory variables that have a demonstrated ability to predict future returns. Our tests are also designed to ensure these variables represent fresh news, which was recently released at the time when the stock recommendations themselves were issued.

We find that analysts generally prefer growth stocks that display glamour characteristics. Stocks that receive higher recommendations have positive price momentum and high trading volume (as measured by the turnover ratio). They exhibit greater past sales growth, and are expected to grow their earnings faster in the future. These stocks also have higher valuation multiples, more positive (income increasing) accounting accruals, and are investing a greater proportion of their total assets in capital expenditures.

Overall, analysts favor growth firms that appear over-valued by traditional valuation metrics.

In the second part of the study, we evaluate the implications of these analyst preferences for the returns prediction ability of their recommendations. Like earlier studies (e.g., Elton et al. (1986), Womack (1996), and Barber et al. (2000)), we find that analyst recommendations have predictive power for subsequent returns. Specifically, firms that receive more favorable (less favorable) recommendations earn significantly higher (lower) market adjusted returns over the next six to 12 months. This result holds across all four measures of analyst recommendations: consensus recommendations, individual recommendations, and the *changes* in each of these variables.

More importantly, we find that analysts' recommendations generally run counter to a predictive variable's normative usage in returns prediction. For seven out of our eight predictive variables, the correlation with analysts' stock recommendations is directionally opposite to the variable's correlation with future returns. In multivariate regressions, we find that these explanatory variables can explain a significant proportion of the cross-sectional variation in analyst recommendations. However, most of these variables are correlated with analyst recommendations with the "wrong" sign, suggesting that analysts do not incorporate the large-sample predictive attributes of these variables in their recommendations.

The ability of analysts' stock recommendations to predict future returns is surprising, in light of their general disagreement with the other predictive variables. In the last part of the paper, we examine the ability of analyst recommendations to predict returns after controlling for the other eight variables. We find that these eight variables have strong predictive power for returns over our sample period. However, analyst recommendations consistently exhibit incremental predictive power after including these variables.

The predictive power of recommendation *changes* (revisions) is reduced, but not eliminated, after controlling for the other predictive variables. The predictive power of

the *level* of analyst recommendation actually increases after controlling for the other variables. This effect is most pronounced for firms shunned by the quantitative variables. These findings suggest that some of the information contained in analyst stock recommendations, particularly the level of these recommendations, is orthogonal to the information in the other predictive signals.

In sum, our results show that analyst recommendations do not fully integrate the available information about expected cross-sectional returns. In fact, the stocks they recommend most highly tend to bear some of the least favorable characteristics in terms of the other predictive signals. Nevertheless, their recommendations have incremental predictive value for subsequent returns. In our concluding section, we discuss implications of these findings for analysts, and investors who rely on their recommendations.

The remainder of the paper is organized as follows. The next Section describes the motivation for this study and develops our hypotheses in the context of prior studies. Section 3 presents our research methodology and sample selection procedures. In Section 4, we present our empirical results. Section 5 summarizes our findings and discusses some of their implications.

2. Motivation and Hypotheses

Our research is primarily motivated by an underlying desire to better understand the judgment and decision process behind analysts' stock recommendations. Although several recent academic studies show that analyst recommendations have predictive power for subsequent returns (e.g., Elton et al. (1986), Womack (1996), and Barber et al. (2000)), our knowledge of how analysts arrive at these recommendations is startlingly rudimentary. By presenting a descriptive profile of the firms preferred by analysts, we shed light on analysts' consideration of various financial information cues in developing their stock recommendations.[4]

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[4] Our sample consists of firms that have analyst coverage, and have already at least one prior stock recommendation. Therefore, our evidence may not extent to analysts' decision to commence or terminate coverage. For an analysis of these decisions, see McNichols and O'Brien (1997) and O'Brien and Bhushan (1990).

The measures we consider are variables that have a demonstrated ability to forecast cross-sectional returns in prior studies. Our tests serve a dual purpose. First, they allow us to examine the extent to which the predictive power of analyst forecasts is due to analysts' tendency to issue recommendations consistent with various investment strategies. Second, they help us to understand the extent to which analysts fully incorporate concurrently available information in their recommendations. These results should help investors to better understand the usefulness (and limitations) of analyst stock recommendations in investment decisions.[5]

Our study links the literature on analyst recommendations to prior studies on the predictability of cross-sectional returns. The eight predictive variables we examine, discussed in more detail in the next section, are nominated by prior studies in accounting and finance. We evaluate the predictive ability of analyst recommendations in light of these eight variables. Womack (1996) and Elton et al. (1986) show that firms that receive buy (sell) recommendations tend to earn higher (lower) abnormal returns in the subsequent one to six months. Barber et al. (2000) extend the investigation to consensus recommendations, documenting the potential to earn higher returns by buying the most highly recommended stocks and short selling the least favorably recommended stocks. We investigate the extent to which this price drift phenomenon is due to analysts' tendency to issue recommendations consistent with other investment strategies.

Using recent (largely post-1994) data, we confirm prior findings that analyst recommendations predict subsequent returns. More importantly, we show that analysts' preferences, as expressed in these recommendations, are largely orthogonal to the other predictive variables. Controlling for the other variables, the stocks preferred by analysts

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[5] This approach is similar in spirit to Brunswick's lens model analysis, in which a decision-maker assesses various information cues to predict a criterion event (e.g., see Libby (1981) for further discussions).

continue to outperform the stocks they shun. These findings suggest analysts consider a different set of information about the companies that they recommend.[6]

2.1 Predictive Variables

We consider eight variables that have demonstrated their ability to predict cross-sectional returns. The Appendix contains detailed information on how each variable is computed. These variables are also summarized below.

2.1.1 Technical Indicators – The first two explanatory variables are RETP6MO (price momentum) and VOLP6MO (trading volume). RETP6MO is the market-adjusted return for each stock in the six months preceding the month of the recommendation. Prior studies (e.g., Jegadeesh and Titman (1993)) show that firms with higher (lower) price momentum earn higher (lower) returns over the next 12 months. VOLP6MO is the average daily volume turnover for the stock in the six months preceding the month of the recommendation.[7] Lee and Swaminathan (2000) show that high (low) volume stocks exhibit glamour (value) characteristics, and earn lower (higher) returns in subsequent months. If analysts based their recommendations on the predictive attributes of price momentum and trading volume, we would expect past winners and lower-volume stocks (past losers and higher-volume stocks) to receive the most favorable (least favorable) recommendations.

2.1.2 Valuation Multiples – We also consider two valuation multiples: EP (the earnings-to-price ratio) and BP (the book-to-price ratio). Both variables are widely used in value-based investment strategies. Starting with Basu (1977), a number of academic studies show that high EP firms subsequently outperform low EP firms. Similarly, Fama and French (1992), among others, show that high BP firms subsequently earn higher returns than low BP firms. Academic opinions differ on whether these higher returns represent

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[6] Our study is also tangentially related Abarbanell and Lehavy (1999) and Bradshaw (2000). These studies focus on the relation between analyst recommendations and their earnings forecasts. Our main focus is on the task of returns prediction.

[7] The trading volume for NASDAQ stocks is inflated by inter-dealer trades. To adjust for the is effect, we deflate the turnover measure for NASDAQ stocks by a factor of 2 in computing VOLP6MO.

contrarian profits or a fair reward for risk.[8] In either case, if analysts pay attention to the predictive attribute of these multiples, we would expect high EP (and high BP) firms to receive more favorable recommendations.

2.1.3 Growth Indicators – We include two growth indicators: LTG (the mean analyst forecast of expect long-term growth in earnings) and SGI (the rate of growth in sales over the past year). Lakonishok, Shleifer and Vishny (1994) show that firms with high past growth in sales earn lower subsequent returns. They argue that high growth firms are glamour stocks that are over-valued by the market.[9] In the same spirit, La Porta (1996) shows that firms with high forecasted earnings growth (high LTG firms) also earn lower subsequent returns. If analysts rely on these large sample results, low SGI (and low LTG) firms should receive more favorable recommendations.

2.1.4 Fundamental Signals – Finally, we include two fundamental signals from the accounting literature: TATA (total accruals divided by total assets) and CFITA (Cash flow from investments divided by total assets). Sloan (1996) shows that firms with more positive (income increasing) accruals earn lower subsequent returns. He argues that the accrual-component of earnings is less persistent, and that the market does not take this effect into account in a timely fashion. Beneish, Lee, and Tarpley (2000) show that growth firms with high CFITA also tend to earn lower returns. They argue that high CFITA firms are growth firms that tend to over-extend themselves. Again, if analysts pay attention to these results, lower TATA (and lower CFITA) firms should receive more favorable recommendations.

In sum, all eight variables have demonstrated an ability to predict cross-sectional returns in prior studies.[10] While not an exhaustive list, these variables do capture much of what

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[8] See, for example, the discussions in Fama and French (1992) and Lakonishok, Shleifer, and Vishny (1994) for two alternative interpretations of the evidence.

[9] Lakonishok et al. (1994) use a variable that measures the change in sales over the past five years. Our variable is the one-year growth rate in sales, which Beneish (1999) shows is useful in detecting firms that manipulate their earnings.

[10] These prior studies are generally based on pre-1995 data. Since most of our observations are more recent (post-1994), our results also represent out-of-sample tests of these earlier findings.

is known about large-sample tendencies in expected returns. To the extent that analysts are either explicitly or intuitively aware of these tendencies, these variables may be reflected in their stock recommendations. If so, we would expect the variables to be correlated with analyst recommendations in the same way they are correlated with future returns.

3. Sample Selection and Research Design

3.1 Sample Selection

Our initial sample consists of First Call stock recommendations issued during the period from January 1993 to April 1998, inclusively. We require that each sample firm be listed as a common stock in the CRSP database and that its accounting information be available on the merged COMPUSTAT database. These data constraints ensure the availability of basic financial information for each firm in our sample.

We paid particular attention to the timing of the analysts' stock recommendations relative to the availability of other investment signals. To ensure comparability across firms, we focus on companies with a December fiscal year end. For each firm, we select the first stock recommendation issued in the second quarter of the next fiscal year — i.e., in the three-month period from April 1st to June 30th of year t+1 — that also has a prior recommendation from the same brokerage firm. Having only one observation per firm-year avoids the problem of non-independent observations (due, for example, to "herding" among analysts) that can inflate test statistics.[11]

Figure 1 illustrates the data collection periods for each of our empirical measures. For a recommendation issued in the second quarter of year t, we use accounting data from fiscal year t-1. The market-related data (past returns and trading volume) are collected over the six months prior to the month of recommendation. Subsequent return accumulation begins with the first trading day of the month following the

[11] Welch (1999) documents evidence of positive serial correlation in analyst recommendation revisions.

recommendation. These procedures ensure that: (1) the latest annual financial statements are available to the analysts at the time of their recommendation, (2) this financial information is reasonably fresh for all sample firms, (3) firms just added to the analysts' following are excluded, and (4) future returns reflect potentially tradable strategies.

We examine two types of recommendations — the first *individual* analyst's recommendation during the recommendation collection period, and the *consensus* (mean) recommendation on the same date. Individual recommendations are fresher, and more likely to reflect recent news. However, consensus judgments are generally less noisy than the individual experts that comprise the consensus. We report key results for both recommendation metrics. In addition, we investigate the *change in* (revision to) both types of recommendations.

3.2 Data Description

Our data collection procedure yielded a total of 4,895 individual recommendations (and related consensus recommendations) over six years. Table 1 provides descriptive statistics on the number of observations by year (Panel A), by exchange (Panel B), by NYSE size decile (Panel C), and by industry (Panel D). Panel A shows that over 90% of our observations are from 1994-1997. Panel B shows that approximately 56% (42%) of our observations consists of NYSE (NASDAQ) firms. Panel C shows these observations are evenly distributed across the NYSE size deciles, but that size varies by exchange. Finally, Panel D shows that these firms span a large number of different industries, with no single industry representing more than 8% of the total sample.

Table 2 reports information on the distribution of the consensus and individual analysts' recommendations. To allow for a more intuitive interpretation of the quantitative results, we code the recommendations so that more favorable recommendations receive a higher score (e.g., 5=strong buy, 1=strong sell). The left-side of Panel A reports descriptive statistics for five consensus recommendation quintiles. The right-side of Panel A reports descriptive statistics for four categories for individual recommendations. It is clear from these results that analysts rarely issue sell or strong-sell recommendations. Only 224 out

of 4,895 individual recommendations (less than 5%) were sells or strong-sells. Similarly, the mean consensus recommendation in the bottom consensus quintile is only a hold (3.10).[12]

Panel B reports the *change* in analyst recommendations, defined as the current recommendation minus the prior recommendation. For changes in the consensus recommendation, we report descriptive statistics by quintile. For changes in individual recommendations, we report results by three categories: increases, no change, and decreases. In our sample, analysts were slightly more likely to downgrade a firm than upgrade it (2,214 versus 1,929). Around 15% (752 out of 4,895) of the individual recommendations were unchanged from the previous recommendation.

Panel C provides evidence on the negative correlation between the level of the prior consensus recommendation, and *changes* in the consensus. A firm that received a relatively high (low) prior recommendation is much more likely to be down (up) graded. For example, 51.3% of the firms in the top quintile in terms of the prior consensus were then in the bottom quintile in terms of *changes* in the consensus recommendation. Conversely, 48.6% of the firms in the bottom quintile of prior consensus recommendations were then in the top *changes* quintile. In subsequent tests, we control for this strong negative correlation.

Figure 2 provides information on the duration (age) of the prior recommendation at the time of the new recommendation. This information provides us with a reasonableness check on the frequency of the revisions. Figure 2a reports the number of calendar days outstanding by deciles. This figure shows that a recommendation is, on average, 259 days old when it is revised. Figure 2b reports the average number of days outstanding by recommendation type. It shows that across all five categories of recommendations, the

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[12] Commerical services that report analyst recommendations (e.g., First Call and IBES), generally assign a lower score to more favorable recommendations (i.e., 1=strong buy, 5=strong sell). To reconcile our score with the score reported by these services, subtract our score from 6. For example, the mean consensus recommendation in our sample is equivalent to a rating of 2.2 (6.0 - 3.8) in First Call. The mean consensus in the bottom quintile is equivalent to a First Call rating of 2.9 (6.0 – 3.1).

average age of the recommendations is fairly stable – between 206 and 286 days. Apparently analysts typically revise their recommendations every 6 to 10 months. This evidence provides justification for examining future returns over a similar holding period. It also offers some assurance that our data do not contain redundant or omitted recommendation revisions.[13]

4. Empirical Results

4.1 Analyst Recommendations and Future Returns

Table 3 provides evidence on the predictive ability of analyst stock recommendations. We find similar results for 3, 9, or 12 month holding periods. In general, results are strongest for returns over the first three-month holding, and gradually weakens over time. However, for parsimony, we only report results for a six-month holding period. Recall that each observation represents a single firm-year, thus avoiding analyst "herding" behavior and other non-independence problems.

Panel A documents the Spearman rank correlation between the four recommendation measures and market-adjusted returns for the six months following the month of recommendation (RETF6MO). All four measures are positively correlated with future returns. The *level* of the recommendation is less correlated with subsequent returns than the *changes* in recommendation, with the consensus recommendation having the lowest correlation.

The next two panels report the mean and median market-adjusted return by analyst recommendation *level* (Panel B), and by the *change* in analyst recommendation (Panel

[13] Two possible concerns with recommendation data are: 1) What appear as revisions in the data may not be new recommendations, but are automatically generated by the data capture system, and 2) First Call estimate files only capture recommendations when there has been an earnings estimate revision (Welch, 1999). The first problem results in too many revisions, the second results in too few. As discussed with S. Levine (Director of Quantitative Research at First Call Corporation), the recommendation dataset we used contains only recommendation revisions that are instigated by a brokerage firm, and captures recommendation revisions without requiring an accompanying estimate revision.

C). For all four measures, firms that receive more favorable recommendations (buys or upgrades) earn higher subsequent returns than firms that receive less favorable recommendations (sells/holds or downgrades). For the consensus recommendations, the mean difference between top and bottom quintile is around 3% over the next six months, with most of the returns coming from the under-performance of the least preferred firms. For individual recommendations, top and bottom groups differed on average by around 4% over the next six months, again with most of the difference coming from the poor showing of the sell/hold firms. Overall, our findings confirm prior studies that show analyst recommendations have predictive power for subsequent returns. [14]

4.2 Other Investment Strategies

Table 4 reports the relation between future returns and other investment strategies. Panel A shows the Spearman rank correlation between each variable and RETF6MO. Over our sample period, all eight variables are significantly correlated with future returns in the direction reported in prior studies. In general, firms with positive price momentum (RETP6MO) and low trading volume (VOLP6MO) earned higher market-adjusted returns over the next six months. Similarly, high EP and BP firms, low LTG and SGI firms, low CFITA and TATA firms, earned higher subsequent returns. The highest absolute correlations are with price momentum (RETP6MO), the expected long-term growth (LTG), the earnings-to-price ratio (EP), and past trading volume (VOLP6MO). These correlation levels range from +0.156 (RETP6MO) to -0.118 (LTG).

We also compute an aggregate indicator measure (FScore) and evaluate its predictive power for future returns. To construct this variable, we first convert each of the eight individual indicators into a binary signal. For variables that are positively (negatively) correlated with future returns, we assigned a value of 1 if it is higher (lower) than a threshold value, and 0 otherwise. Missing values are coded as ½.

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[14] Our results are similar in magnitude to the findings in Womack (1996), who used an earlier sample period. Compared to his study, we may understate total returns because our holding period does not begin until the beginning of the next calendar month. Barber et al. (2000) and Elton et al. (1986) test somewhat different implicit strategies, making direct comparisons more difficult.

The cutoff value for each variable is listed in the Appendix. These values are determined based on general information gleaned from past periods. For example, we used 0% for the market-adjusted return price momentum measure (RETP6MO). We used 22 basis points as the cutoff for trading volume because it represented the mean daily turnover on the NYSE for the 10 years prior to the sample period (from the 1996 NYSE Fact Book). The FScore for each firm-year is the sum of the binary explanatory variables.

Under the heading "Distribution", Panel A reports the percent of total observations that received a value of "1", or "1/2", or "0", for each explanatory variable. The right-most column in Panel A reports the Spearman rank correlation of these binary variables with RETF6MO. As expected, correlation levels are slightly lower when we move from the continuous variable to this binary coding. However, the binary versions of all eight variables still exhibit statistically significant correlations with future returns at the 1% level. The bottom right cell of this panel reports the Spearman rank correlation between the FScore and RETF6MO. This aggregate signal had a positive Spearman correlation with future returns of 0.1592.

Panel B reports the mean and median market-adjusted return for firms grouped by their FScore. During our sample period, a majority of U.S. firms under-performed the value-weighted market index. However, firms in the top three FScore groups out-performed the market by a mean of 1.78% over the next six months. Conversely, firms in the bottom three FScore groups had a mean market-adjusted return of –5.28% over the next six months. The difference in mean returns between the top and bottom groups (High – Low) is 7.06%. The difference in median returns is 10.65% over six months. Both are statistically significant at less than 1% using two-tailed tests. Clearly, FScore is a useful predictor of returns during our sample period.

4.3 Analyst Recommendations and Investment Strategies

Thus far, we have established the predictive ability of the eight investment indicators in our sample. We have also documented the predictive ability of the analyst stock

recommendations. In this section, we document the relation between analyst recommendations and the predictive variables nominated by the investment strategies.

Table 5 reports the mean and median value of each of the eight investment indicators by consensus recommendation quintile. Under the heading "Normative Direction," we show the direction of correlation between each variable and future market-adjusted return (from Table 4A). Under the heading "Actual Direction" we report the direction of correlation between that variable and the analysts' consensus recommendation. We report the Spearman rank correlation between each variable and the consensus recommendation. In addition, we provide the Wilcoxon Chi-square statistic for a test of the null that the median value is the same for the top and bottom consensus recommendation quintile.

The most striking result in Table 5 is the consistency with which analyst stock recommendations contradict the expected normative usage of these variables. In seven out of eight cases, the actual direction of the analysts' preference is opposite to the normative direction for predicting future stock returns. Analysts prefer stocks with high recent turnover (trading volume) over stocks with low turnover. They also prefer low EP, low BP, high LTG, high SGI, high CFITA, and high TATA stocks. In fact, the only variable that analysts seem to get "right" is price momentum – they prefer stocks that have been recent winners over stocks that have been recent losers.

Tables 6 and 7 provide additional evidence in a multivariate setting. These tables report results when each recommendation variable is regressed on the eight explanatory variables.[15] Table 6 reports results when the dependent variable is the *level* of the recommendation. With few exceptions, Table 5 results hold in the multivariate setting. Panel A shows that the continuous version of these eight variables explains 27% of the cross-sectional variation in the consensus recommendation. However, except for

[15] The dependent variable in Panel B is categorical. For simplicity, we report OLS regression results. However, the direction of the estimated coefficients and their statistical significance are unchanged when we use an Ordered Logit model.

RETP6MO and EP, these variables load with the opposite sign from their normative usage. The results are similar using the binary signals. In fact, the FScore is strongly negatively correlated with analyst recommendations, with an r-square of 13.1%.

Moving from the consensus recommendation (Panel A of Table 6) to individual recommendations (Panel B of Table 6) reduces the overall explanatory power of the model, but not the relation between most individual signals and the recommendations. Overall, Table 6 shows that only RETP6MO, EP, and TATA appear with the right sign. Table 7 confirms these results using *changes* in recommendations rather than the level of the recommendation as the dependent variable. In these regressions, we control for the prior level of the analyst recommendation. Again, we see the same pattern of correlations for the investment signals. The FScore variable is also significantly negatively correlated with analyst recommendations.

In sum, these findings show that analyst recommendations tend to be negatively correlated with the other predictive variables in their normative usage. Given these findings, it seems unlikely that the predictive power of analyst recommendations is due to their reliance on information cues derived from these variables. We explore this question more directly in the next section.

4.4 The role of analyst recommendations in returns prediction

In this section, we evaluate the role of analyst recommendations in returns prediction, after controlling for the other predictive variables. Table 8 reports results of a bi-dimensional analysis, in which firms are sorted by their FScore, as well as by their analyst recommendation. Panel A of this table reports results for the *level* of the consensus recommendation. Panel B reports results for individual recommendations. Panels C and D report results for the *change* in consensus and the *change* in individual recommendations, respectively.

The first result from this table is that both signals have incremental predictive power. Looking along the bottom row of each panel, it is clear that the FScore variable has

significant predictive power for returns after controlling for the analyst recommendation. High FScore firms earn higher subsequent returns in all analyst recommendation categories, significantly higher in 13 out of 17 categories. The results along the right column of each panel show that analyst recommendations also have some predictive power after controlling for FScore. Firms preferred by analysts earn higher returns in all 12 FScore categories. In 8 categories, the return differential is statistically significant. Interestingly, the *level* of the consensus recommendation appears to have the highest incremental power for returns prediction.

The second result is that when analyst recommendations and the FScore signal disagree, the FScore signal tends to dominate. The cells in along the main diagonal of each panel (toward the upper-left and lower-right corners) report mean returns when the FScore and the analyst recommendation signals are in disagreement. In all four panels, firms in the upper-left corner (High FScore firms with low recommendations) earn higher average returns than firms in the lower-right corner (Low FScore firms with high recommendations). Evidently, when the two signals conflict, the FScore results in more reliable returns predictions.

Third, when the two signals agree, we find the highest predictive power for returns. In the lower-right corner of each panel, we report the return differential when analyst recommendations are combined with the FScore indicator. These cells show the mean return differential between firms with the best recommendations and highest FScores (Best-High), and firms with the worst recommendations and lowest FScores (Worst-Low). In all four panels, the Best-High group earns higher returns than the Worst-Low group. The returns differential ranges from 7.1% to 18.6% over the next six months, which is greater than returns earned by considering either signal alone.

Figure 3 depicts the cumulative excess return from various hedge strategies involving both analyst recommendations and the FScore. The High-Low strategy involves taking an equal-weighted long position in the top FScore quintile firms and short selling an equal-weighted position in the bottom FScore quintile firms. The Best-Worst strategy

involves buying the highest recommended firms and selling the lowest recommended firms. The Combined strategy buys the Best-and-High group and sells the Worst-and-Low group. The results for the six-month holding period are the same as those reported in Table 8. In addition, Figure 3 reports the results for 3 to 15 month holding periods. The main results are robust to these variations in the holding period.

It is clear from these graphs that all four types of analyst recommendations have some predictive power for returns, particularly over the next 3 to 9 months (see Best-Worst results in each graph). However, these four measures differ in terms of their incremental contribution in combination with FScore (see Combined results in each graph). Clearly the *level* variables contribute more to the combined strategy than the *change* variables. The level of the consensus forecast, in particular, seems to have the potential to significantly enhance the predictive power of the simple FScore strategy.

Finally, Table 9 provides a general analysis of the correlation between future returns and all the explanatory variables. The table values represent the estimated coefficients (and test statistics) from a series of regressions in which the dependent variable is the market-adjusted return for the six months following the month of the recommendation (RETF6MO). The independent variables are the level of the recommendation, the change in the recommendation, the FScore, the eight binary explanatory variables, and the eight continuous explanatory variables. For the binary explanatory variables, we report the average estimated coefficient across all eight variables, as well as the F-statistic from a test of the null that these variables have no explanatory power. For the continuous explanatory variables, we do not report an estimated coefficient. However, we do report the corresponding F-statistic.

Panel A reports the results for the consensus recommendation and changes in the consensus recommendation. Models 1A to 1D examine the predictive power of the consensus recommendation controlling for the other variables. Model 1A shows that the level of the consensus has some predictive power for future returns. Notice that the estimated coefficient and the t-statistic on the consensus recommendation both *increase*

as we introduce the FScore and the binary variables (Models 1B and 1C). The estimated coefficient is also higher in Model 1D, but the number of observations drops and so does the t-statistic. Evidently the predictive power of the consensus recommendation improves after controlling for the other variables. The estimated coefficient is interpretable as the return differential between the top and bottom quintile. The results show that the top consensus quintile outperforms the bottom consensus quintile by 5 to 6.5 percent over the next six months, even after controlling for the other variables.

Models 2A to 2D report results for the change in the consensus recommendation. The predictive power of this variable is reduced as we introduce the other variables, suggesting that recommendation revisions are related to the other signals. However, the revision measure remains positive in all four models, and is statistically significant for all except Model 2D. Overall, even changes in the consensus recommendation seem to contain useful information not fully captured by the other variables.

Models 3A to 3D report results when both the level and the change variables are included. Model 3A shows that the change variable is useful when only the recommendation level is in the model; when we introduce the other variables, the change variable loses its incremental usefulness. In all the specifications, the level of the consensus recommendation is incrementally useful for returns prediction.

Panel B repeats this analysis for individual recommendations. The overall results are qualitatively the same as those for the consensus recommendation. Again, we see that the predictive power of the level recommendation variable generally *increases* with the introduction of the other explanatory variable (Models 1A to 1D). The change in recommendation variable has incremental power for predicting returns even with the inclusion of all eight continuous variables (Models 2A to 2D). Finally, when both the level and the change variables are included (Models 3A to 3D), the level of the recommendation has generally superior incremental power to predict returns.

In sum, Tables 8 and 9 show that the predictive power of analyst stock recommendations does not derive from their correlation with the other explanatory variables. Despite the fact that analysts tend to go "against the odds" in 7 out of 8 cases, their recommendations seem to offer some information useful in predicting near-term stock returns (over the next 6 months). The incremental usefulness for returns prediction is most pronounced for the level of the consensus recommendation.

5. Conclusion

In making a stock recommendation, financial analysts explicitly express their expectation about the relative near-term return performance of a given firm. In this study, we examine the relation of their recommendations to other concurrently available public information. In particular, we focus on variables that prior studies show have some predictive power for future returns. Our goal is to better understand how the activities of financial analysts affect capital market efficiency.

We find that analysts prefer growth stocks that appear over-valued by traditional measures. The stocks that receive more favorable recommendations typically have more positive price momentum, higher trading volume (turnover), higher past and projected growth, more positive accounting accruals, and more aggressive capital expenditures. In short, analysts seem to recommend a set of stocks that are quite different from the stocks that would have been nominated by quantitative investment strategies. In fact, the correlation between analyst recommendations and an aggregate measure of these variables is reliably negative.

Despite its negative correlation with these variables in their normative usage, analyst stock recommendations still have significant predictive power for returns. Controlling for the other variables, we find that firms favored by analysts tend to outperform firms that are less favored. In fact, the explanatory power of the mean analyst recommendation increases when it is used in conjunction with the other variables. This finding suggests that the return-relevant information contained in analyst recommendations is, to some degree, orthogonal to the information contained in the other variables.

Our analysis sheds no further light on the exact nature of the incremental information that analysts incorporate in their recommendations – information which the market appears to react to with a lag. Since we do not control for industry-related effects, it is possible that their stock recommendations reflect news about a firm's competitive position in its industry. These recommendations may also capture qualitative aspects of a firm's operations (e.g., managerial abilities, strategic alliances, intangible assets, or other growth opportunities) that do not appear in the quantitative signals we examine. The evidence is at least consistent with the analysts' claim that they bring new information to market.

An alternative hypothesis is that the recommendations themselves cause the subsequent price drift through the publicity surrounding them, and the subsequent marketing of these stocks by the affiliated sales forces. In this scenario, analysts do not actually bring new information to market via their research efforts. One way to test this hypothesis is to check for return reversals over longer horizons. However, given our limited sample period, it would be difficult to distinguish this scenario from the one in which analysts are facilitating the price formation process. We regard this as an interesting area for further research.

Our results suggest that financial analysts may be able to improve their stock recommendations by paying more attention to the large sample attributes of expected returns. We have identified a number of specific signals that analysts do not generally incorporate into their recommendations. If their disregard for these signals is not deliberate, our results may help analysts to improve their future recommendations. Specifically, our results suggest that if analysts want to generate recommendations with greater predictive power for returns, they should grant more favorable recommendations to firms with lower trading volume, higher EP and BP ratios, lower LTG and SGI measures, more negative (income decreasing) accruals, and lower capital expenditures.[16]

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[16] This assumes that our results are not due to incentive problems. For example, if analysts recommend high volume stocks because they are more likely to generate higher trading commissions, they are unlikely to modify their recommendations in light of our findings. The integration of these signals into

From an investment perspective, our results suggest analyst recommendations play a dual role in the price formation process. On the one hand, they appear over-enamored with growth and glamour stocks. To the extent that their opinion affects public sentiment, this evidence is at least consistent with the view that they contribute to noise trading in the market. On the other hand, these findings suggest sell-side recommendations can still play a useful role in quantitative strategies. When analyst recommendations conflict with a combined investment signal (the FScore), the FScore dominates. However, within individual FScore categories, the recommendations are incrementally useful in returns prediction. The consensus recommendation, in particular, has significant ability to forecast near-term (3 to 9 month) cross-sectional returns.

In contemplating its usage in investment strategies, readers need to consider risk and transaction costs issues not fully explored in this study. It is possible that the top quintile stocks are riskier than the bottom quintile stocks along some unknown dimension. This possibility is made less likely by our inclusion of a wide set of control variables known to be associated with expected returns. Nevertheless, the possibility cannot be ruled out. In addition, we have not included transaction costs, which will vary by investment style.

To summarize, our results suggest that fundamental analysts and investment houses that employ large-sample quantitative techniques could each learn something from the other. Behavioral research shows that, in many cases, the combination of a human decision-maker and a mechanical decision-aid produces the best performance (see, e.g., Blattberg and Hoch (1990)). Assuming they are interested in predicting intermediate-horizon (3 to 12 month ahead) returns, sell-side analysts may wish to pay more attention to the results of large-sample studies. On the other hand, quantitative investors may also benefit by augmenting their stock selection process with the consensus recommendation of sell-side analysts.

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analysts' recommendations may also be hindered by psychological factors, such as analysts' relative confidence in their own judgments (Nelson, Krische, and Bloomfield (2000)).

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APPENDIX: Investment Signals

This appendix provides a detailed description of the eight investment signals used in the study. All these variables were windsored at the 1st and 99th percentiles, based on the 1993-1996 sample. All missing values are coded as ½ for the binary variables. [*text*] refers to the data source, where D# is the item number from Annual Compustat.

Variable	**Description**	**Calculation Detail *[Source]***
RETP6MO	Cumulative market-adjusted return for a stock in the 6 months preceding the month of recommendation	$\prod_{i=m-6}^{m-1}$ (1+monthly return$_i$ – value-weighted mkt return$_i$)–1, where m = month of recommendation in year t *[CRSP]* *Binary variable: = 1 if RETP6MO is greater than 0, zero otherwise.*
VOLP6MO	Average daily volume turnover for a stock in the six months preceding the month of recommendation	$\frac{\sum_{i=1}^{n} \text{Daily volume}/\text{Shares Outstanding}}{n}$, where n = number of days available for 6 months preceding the month of recommendation (months m–1 to m–6, where m=month of recommendation in year t) *[CRSP]* *Binary variable: =1 if VOLP6MO is less than 22 bp (approximate mean daily turnover for NYSE firms for 1986-95), zero otherwise.* *NYSE Factbook (1996)*
EP	Earnings to price	EPS$_{t-1}$ / Price$_t$, where EPS$_{t-1}$ = EPS excluding extraordinary items for year *t-1* [D58]; Price$_t$ = Price at end of March of year *t [CRSP]* *Binary Cutoff:=1 if EP greater than 0.04 (approximate NYSE average earning yield over prior 10 years, zero otherwise.* *NYSE Factbook (1996)*
BP	Book to price	Book per share$_{t-1}$ / Price$_t$, where Book per share$_{t-1}$ = [D60] for year *t-1* / [D54] for year *t-1*, Price$_t$ = Price at end of March of year *t [CRSP]* *Binary Cutoff: =1 if BP greater than 0.5 (approximate prior period average for 1976-1993), zero otherwise.* *Frankel and Lee (1998)*
LTG	Long-term growth estimate	Mean long-term growth forecast in most recent consensus available at the end of March of year t *[First Call]* *Binary Cutoff: =1 if LTG less than 12% (approximate prior period average for 1990-1995), zero otherwise.* *IBES*
SGI	Sales growth index	Sales$_{t-1}$ [D12] / Sales$_{t-2}$ [D12] *Binary Cutoff:=1 if SGI less than 1.15 (approximate prior period average for 1982-92), zero otherwise.* *Beneish (1999)*
CFITA	Cash from investing to total assets	(CFI$_{t-1}$ [D311] /Total Assets$_{t-1}$ [D6]) × (–1) *Binary Cutoff:=1 if CFITA less than 10% (approximate prior period average for 1990-1995), zero otherwise.* *Compustat*
TATA	Total accruals to total assets	$\frac{\left\{\begin{array}{l} \langle(\text{Current Assets}_{t-1} - \text{Current Assets}_{t-2}\ [D4]) - (\text{Cash}_{t-1} - \text{Cash}_{t-2}\ [D1])\rangle \\ - \langle(\text{Current Liabilities}_{t-1} - \text{Current Liabilities}_{t-2}\ [D5]) - (\text{Current LTD}_{t-1} - \text{Current LTD}_{t-2}\ [D44])\rangle \\ - (\text{Deferred taxes}_{t-1} - \text{Deferred taxes}_{t-2}\ [D74]) \\ - \text{Depreciation and amortization}_{t-1}\ [D14] \end{array}\right\}}{\text{Total assets}_{t-1}\ [D6]}$ *Binary Cutoff:=1 if TATA less than -3% (approximate prior period average for 1962-91), zero otherwise.* *Sloan (1996)*

FIGURE 1

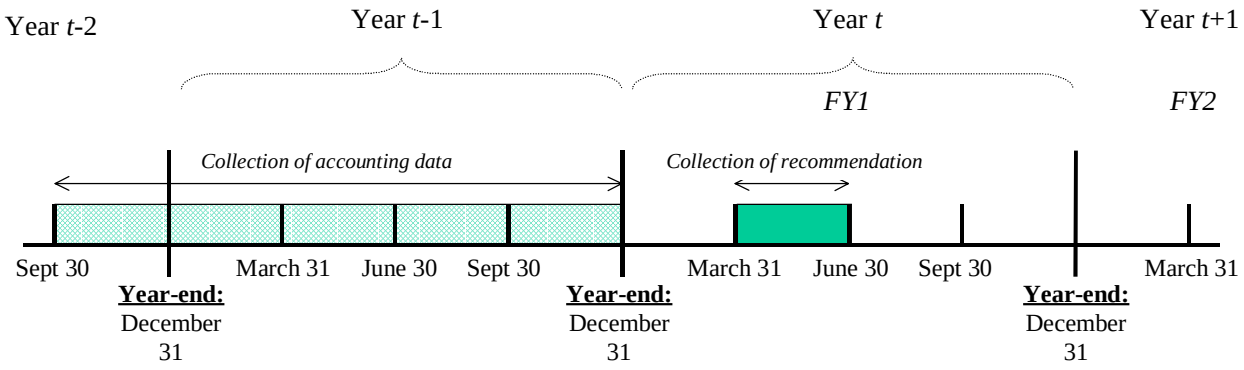

FIGURE 1a. **Timeline depicting data period for the analysts' recommendation and related accounting variables**

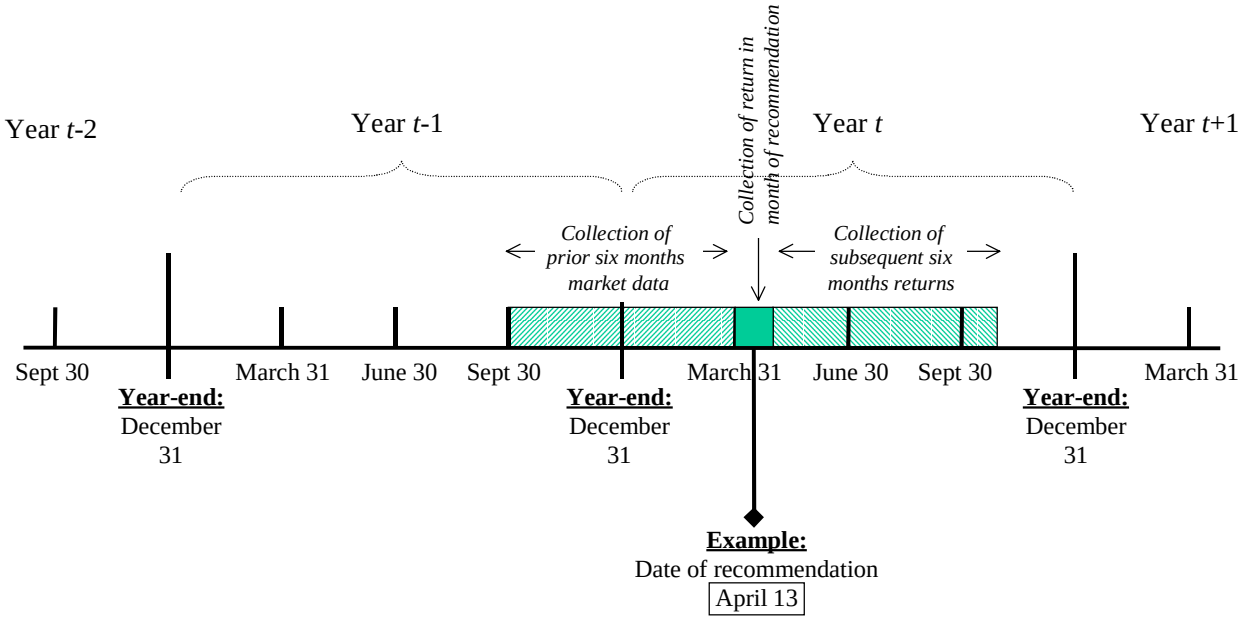

FIGURE 1b. **Timeline depicting data period for the analysts' recommendation and related market variables**

FIGURE 2

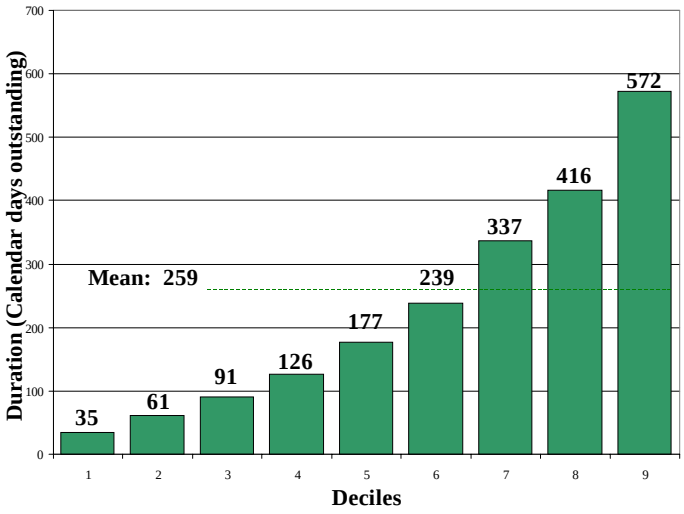

FIGURE 2a. Prior Recommendation Duration (Calendar Days Outstanding)

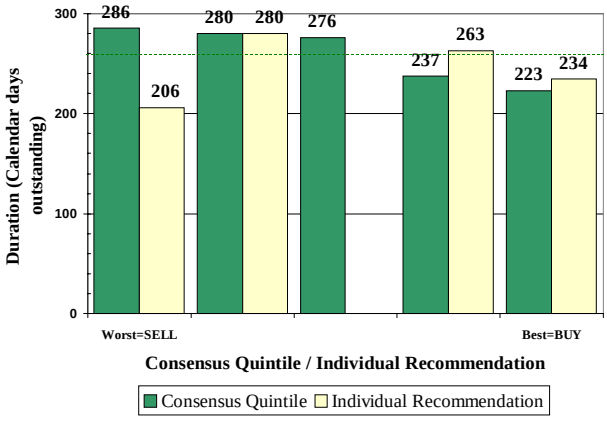

FIGURE 2b. Prior Recommendation Duration (Calendar Days Outstanding) by Current Recommendation Type

FIGURE 3: Cumulative Excess Returns Based on Analyst and FScore Strategies

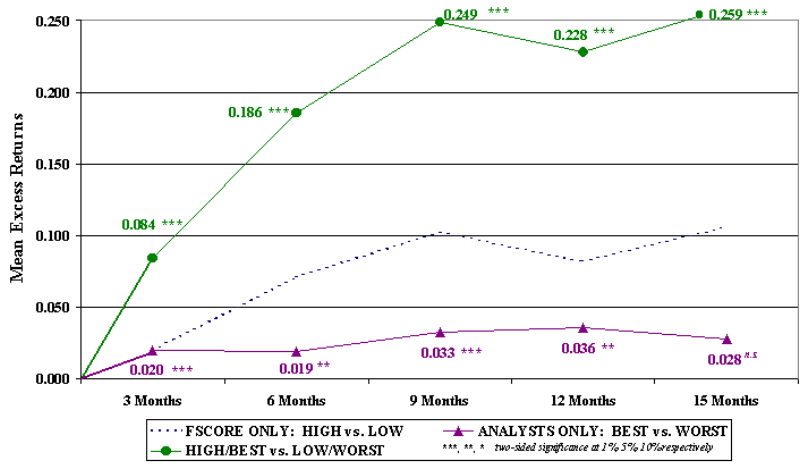

FIGURE 3a. Excess Market-Adjusted Returns on Consensus and FScore

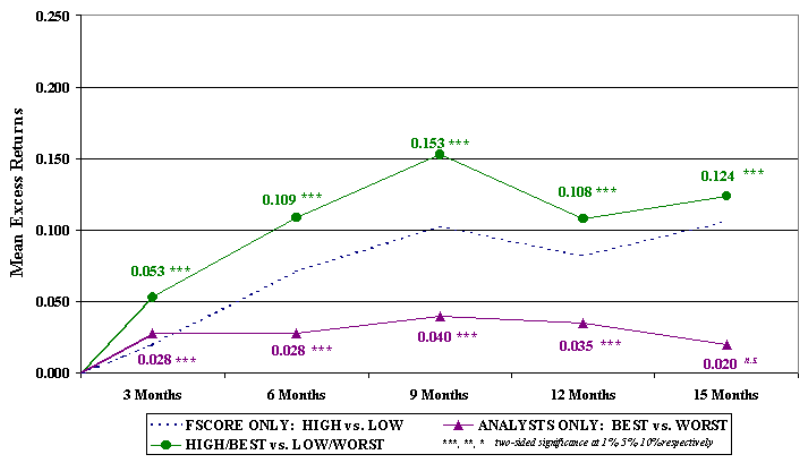

FIGURE 3b. Excess Market-Adjusted Returns on Individual Recommendations and FScore

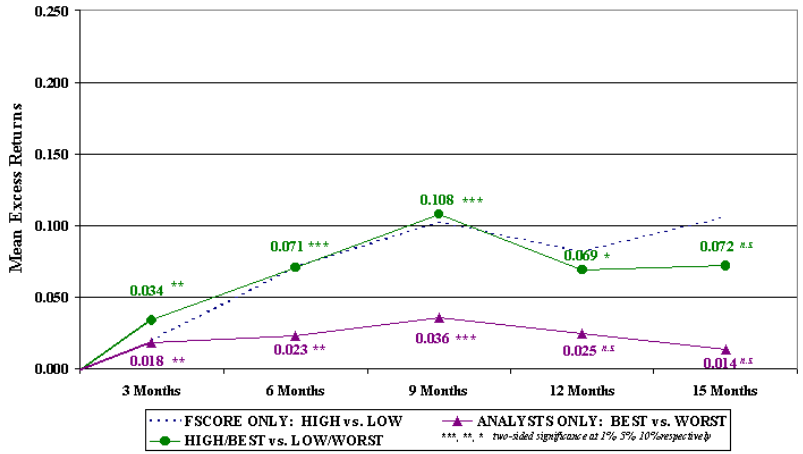

FIGURE 3c. Excess Market-Adjusted Returns Based on Change in Consensus and FScore

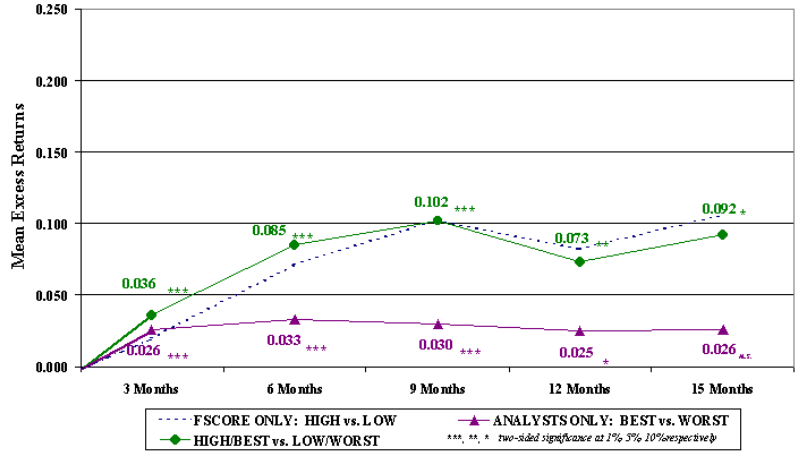

FIGURE 3d. Excess Market-Adjusted Returns Based on Change in Individual Recommendations and Fscore

Table 1: Description of Sample Firms

This table provides descriptive statistics on the firms included in our sample. Our sample consists of December fiscal year end firms in the First Call Recommendations database with sufficient CRSP and Compustat data. The First Call recommendation database we used covers the period 1993–1998 (ending April 3, 1998). We examine the first recommendation revision for each firm in the April 1st to June 30th period of the year after each fiscal year end, thus ensuring only one recommendation per firm-year. Industries are represented by 2-digit SIC Codes. An industry is listed separately if it represents one percent or more of the total sample.

PANEL A: Year

	Sample	
Year	Obs	%age
1993	28	0.6%
1994	769	15.7%
1995	1,084	22.1%
1996	1,256	25.7%
1997	1,410	28.8%
1998	348	7.1%
Total	4,895	100.0%

PANEL B: Exchange

	Sample	
Year	Obs	%age
NYSE	2,723	55.6%
NASD	2,063	42.1%
AMEX	104	2.1%
Other*	5	0.1%
Total	4,895	100.0%

* 4 observations suspended from NYSE or AMEX,
1 observation not traded on NYSE, AMEX, or NASDAQ

PANEL C: NYSE Size Decile

NYSE Mkt Cap Decile	Mean Capitalization ($000's)	NYSE firms		All other firms		Sample	
		Obs	%age	Obs	%age	Obs	%age
1 (Largest)	17,535,889	522	19.2%	21	1.0%	543	11.1%
2	4,304,499	447	16.4%	44	2.0%	491	10.0%
3	2,334,059	380	14.0%	77	3.5%	457	9.3%
4	1,378,744	315	11.6%	95	4.4%	410	8.4%
5	876,840	276	10.1%	136	6.3%	412	8.4%
6	580,922	240	8.8%	192	8.8%	432	8.8%
7	388,542	197	7.2%	232	10.7%	429	8.8%
8	244,871	165	6.1%	330	15.2%	495	10.1%
9	132,884	116	4.3%	500	23.0%	616	12.6%
10 (Smallest)	54,954	65	2.4%	545	25.1%	610	12.5%
Total	2,917,863	2,723	100.0%	2,172	100.0%	4,895	100.0%

Table 1: Description of Sample Firms (Continued)

PANEL D: Industry

Two-Digit SIC Code	Description	Sample Obs	Sample %age
67	Holding, Other Invest Offices	387	7.9%
73	Business Services	360	7.4%
28	Chemicals & Allied Products	346	7.1%
36	Electr, Oth Elec Eq, Ex Cmp	339	6.9%
49	Electric, Gas, Sanitary Serv	327	6.7%
35	Indl, Comml Machy, Computer Eq	259	5.3%
63	Insurance Carriers	216	4.4%
13	Oil and Gas Extraction	215	4.4%
60	Depository Institutions	190	3.9%
38	Meas Instr, Photo Gds, Watches	182	3.7%
48	Communications	175	3.6%
37	Transportation Equipment	108	2.2%
80	Health Services	98	2.0%
58	Eating and Drinking Places	93	1.9%
50	Durable Goods–Wholesale	89	1.8%
20	Food and Kindred Products	88	1.8%
33	Primary Metal Industries	83	1.7%
26	Paper and Allied Products	80	1.6%
27	Printing, Publishing & Allied	73	1.5%
42	Motor Freight Trans, Warehouse	70	1.4%
61	Nondepository Credit Instn	69	1.4%
87	Engr, Acc, Resh, Mgmt, Rel Svcs	68	1.4%
34	Fabr Metal, Ex Machy, Trans Eq	67	1.4%
29	Pete Refining & Related Inds	58	1.2%
51	Nondurable Goods—Wholesale	58	1.2%
45	Transportation by Air	54	1.1%
30	Rubber & Misc Plastics Prods	51	1.0%
70	Hotels, Other Lodging Places	48	1.0%
	Other	644	13.2%
Total		4,895	100.0%

Table 2: Description of Analyst Recommendations

This table provides descriptive statistics on the analyst recommendations in our sample. Each individual recommendation is reverse-scored numerically from 5 (strong buy) to 1 (strong sell). The consensus recommendation is the average of all outstanding recommendations at the time the individual recommendation was issued. Panel A reports summary statistics for the *level* of the recommendation. Panel B reports summary statistics for the *change* in the recommendation. Panel C provides evidence on the correlation between prior consensus levels and changes in the consensus recommendation. The shadings in the last panel signify that greater than 20% of the observations in the conditional distribution appears in that cell.

PANEL A: Analyst Recommendation Level (Str.BUY=5, BUY=4, HOLD=3, SELL=2, Str.SELL=1)

Consensus Quintile						Individual					
Category	Lower Bound	Coded as	Obs	Mean	Std Dev	Category	Lower Bound	Coded as	Obs	Mean	Std Dev
Best=BUY	4.29	1.00	995	4.56	0.224	Best=BUY	Str.BUY = 5	1.00	1,254	5.00	0.000
	4.00	0.75	1,126	4.08	0.095		BUY = 4	0.75	1,726	4.00	0.000
	3.69	0.50	819	3.82	0.078				—	—	—
	3.38	0.25	987	3.54	0.089		HOLD = 3	0.25	1,691	3.00	0.000
Worst=SELL	1.00	0.00	968	3.10	0.250	Worst=SELL	SELL = 2 or 1	0.00	224	1.61	0.488
Total			4,895	3.83	0.525	Total			4,895	3.80	0.913

PANEL B: Change in Analyst Recommendation (Change = Current – Prior)

Consensus Quintile						Individual					
Category	Lower Bound	Coded as	Obs	Mean	Std Dev	Category	Lower Bound	Coded as	Obs	Mean	Std Dev
Best=Increase	0.25	1.00	1,050	0.60	0.404	Best=Increase	Increase = +	1.00	1,929	1.26	0.473
	0.05	0.75	923	0.13	0.056				—	—	—
	-0.08	0.50	991	-0.02	0.034		No change = 0	0.50	752	0.00	0.000
	-0.33	0.25	1,018	-0.20	0.074				—	—	—
Worst=Decrease	-3.00	0.00	913	-0.78	0.427	Worst=Decrease	Decrease = –	0.00	2,214	-1.28	0.494
Total			4,895	-0.04	0.521	Total			4,895	-0.08	1.247

PANEL C: Change in Consensus, Conditioned on Prior Consensus Level

Prior Consensus Quintile	**Change in Consensus Quintiles**					Total
	Decrease				**Increase**	
Best = BUY	506	239	94	78	70	987
	51.3%	24.2%	9.5%	7.9%	7.1%	
	269	304	305	227	245	1,350
	19.9%	22.5%	22.6%	16.8%	18.1%	
	44	156	175	178	56	609
	7.2%	25.6%	28.7%	29.2%	9.2%	
	74	209	230	256	206	975
	7.6%	21.4%	23.6%	26.3%	21.1%	
Worst = SELL	20	110	187	184	473	974
	2.1%	11.3%	19.2%	18.9%	48.6%	
Total	913	1,018	991	923	1,050	4,895
	18.7%	20.8%	20.2%	18.9%	21.5%	

Table 3: Analyst Recommendations and Future Returns

This table examines the correlation between analyst recommendations and future returns. Future returns are defined as the market-adjusted return in the six months after the month of the recommendation (RETF6MO). Four different measures of analyst recommendations are used: the consensus recommendation (CONS), the individual recommendation (REC), the change in the consensus (CHGCONS), and the change in the individual recommendation (CHGREC). Panel A reports the Spearman rank correlation between each analyst recommendation measure and future returns. We report results for both a continuous measure and a categorical measure of analyst recommendation (see Table 2) Panel B reports future returns for firms grouped by their analyst recommendation, and Panel C reports future returns grouped by the change in the analyst recommendation. ***, **, * indicate two-sided statistical significance at 1%, 5%, and 10%, respectively.

PANEL A: Spearman Rank Correlations with Future Returns

		Continuous Dependent Variable: RETF6MO	
Explanatory Variable	**Obs**	**Continuous Explanatory Variable**	**Categorical Explanatory Variable**
CONSENSUS ("CONS")	4,895	0.0070 *n.s.*	0.0077 *n.s.*
INDIVIDUAL ("REC")	4,895	0.0561 ***	0.0561 ***
CHGCONS	4,895	0.0601 ***	0.0623 ***
CHGREC	4,895	0.0641 ***	0.0699 ***

PANEL B: Market-Adjusted Returns by Analyst Recommendation Level

		Consensus Quintile			Individual		
GROUP	**Coded as**	**Obs**	**Mean Return**	**Median Return**	**Obs**	**Mean Return**	**Median Return**
Best = BUY	1.00	995	–0.0062	–0.0247	1,254	+0.0030	–0.0131
	0.75	1,126	–0.0222	–0.0454	1,726	–0.0217	–0.0305
	0.50	819	–0.0130	–0.0225	—	—	—
	0.25	987	–0.0364	–0.0432	1,691	–0.0386	–0.0453
Worst = SELL	0.00	968	–0.0316	–0.0277	224	–0.0422	–0.0388
BUY – SELL			**+0.0253**	**+0.0030**		**+0.0452**	**+0.0256**
			t =1.74	χ^2 *=0.61*		*t = 2.50*	χ^2 *= 2.67*
			*	*n.s.*		**	*

PANEL C: Market-Adjusted Returns by the Change in Analyst Recommendation

		Consensus Quintile			Individual		
GROUP	**Coded as**	**Obs**	**Mean Return**	**Median Return**	**Obs**	**Mean Return**	**Median Return**
Best = Increase	1.00	1,050	–0.0065	–0.0208	1,929	–0.0062	–0.0172
	0.75	923	–0.0145	–0.0220	—	—	—
	0.50	991	–0.0238	–0.0227	752	–0.0133	–0.0302
	0.25	1,018	–0.0270	–0.0436	—	—	—
Worst = Decrease	0.00	913	–0.0404	–0.0682	2,214	–0.0389	–0.0481
Increase – Decrease			**+0.0339**	**+0.0474**		**+0.0327**	**+0.0309**
			t = 2.21	χ^2 *= 14.73*		*t = 3.53*	χ^2 *= 23.09*
			**	***		***	***

Table 4: Investment Signals and Future Returns

This table examines the relation between future returns (RETF6MO) and various investment signals. RETF6MO is the market-adjusted return in the six months following the month of the recommendation. The eight investment signals are describe in detail in the Appendix. FScore is a composite score based on the sum of eight binary variables (from 0 to +8). Each binary variable is derived from an investment signal with the cutoff value described in the table. For variables that are positively (negatively) correlated with future returns, the binary variable assumes a value of 1 if the explanatory variable is higher (lower) than the cutoff, and 0 otherwise. Missing values are coded as ½. Panel A reports the Spearman rank correlation between RETF6MO and each investment signal. Panel B reports the market-adjusted return for firms grouped by FScore. *** (**) indicates statistical significance at 1% (5%) in two-tailed tests.

PANEL A: Spearman rank correlation with future returns

Explanatory Variable	Obs	Continuous Dependent Variable: RETF6MO					
		Continuous Explanatory Variable	Binary Explanatory Variable				
			Definition	Distribution 1	½	0	Correlation
RETP6MO	4,757	0.1560 ***	*1 if RET > 0%* *0 otherwise*	41.7%	2.8%	55.5%	0.1189 ***
VOLP6MO	4,772	–0.0985 ***	*1 if VOL < 22bp* *0 otherwise*	35.9%	2.5%	61.6%	0.0741 ***
EP	4,857	0.1127 ***	*1 if EP > 4%* *0 otherwise*	58.0%	0.8%	41.2%	0.0881 ***
BP	4,856	0.0481 ***	*1 if BP > 50%* *0 otherwise*	42.1%	0.8%	57.1%	0.0697 ***
LTG	3,946	–0.1181 ***	*1 if LTG < 12%* *0 otherwise*	30.8%	19.4%	49.9%	0.0814 ***
SGI	4,759	–0.0443 ***	*1 if SGI < 15%* *0 otherwise*	50.2%	2.8%	47.0%	0.0464 ***
CFITA	4,376	–0.0770 ***	*1 if CFITA < 10%* *0 otherwise*	49.0%	10.6%	40.4%	0.0587 ***
TATA	3,678	–0.0622 ***	*1 if TATA < –3%* *0 otherwise*	42.6%	24.9%	32.5%	0.0372 ***
FScore	4,895		*Sum of binary explanatory variables*				0.1592 ***

PANEL B: Future Market-Adjusted Returns by FScore

GROUP	FScore	Obs	Mean Return	Median Return
High	8	47	0.0567	0.0137
	7	335	0.0149	–0.0088
	6	725	0.0166	0.0034
	Combined	1,107	+0.0178	+0.0012
Medium	5	943	0.0041	–0.0053
	4	889	–0.0293	–0.0513
	3	802	–0.0558	–0.0709
	Combined	2,634	–0.0254	–0.0356
Low	2	668	–0.0496	–0.0996
	1	380	–0.0530	–0.1224
	0	106	–0.0730	–0.0864
	Combined	1,154	–0.0528	–0.1053
High – Low			**+0.0706 *** **	**0.1065 *** **

TABLE 5: Descriptive Statistics by Consensus Recommendation Quintile

This table examines the relation between the level of the consensus recommendation and eight investment signals. Each signal is described in detail in the Appendix. To construct this table, we sort all firms into quintiles by the level of their mean consensus stock recommendation. Table values represent the mean, median, and number of observations in each consensus quintile. Normative Direction indicates the sign of the variable's correlation with future returns. Actual Direction indicates the sign of the variable's correlation with the consensus recommendation. The Spearman rank correlation reported is between the consensus recommendation and a given investment signal. The Wilcoxon Chi-Square statistic tests the null that the median value for the highest recommendation quintile equals the median of the lowest quintile. *** indicates two-sided significance at 1%.

			Consensus Recommendation Quintile							
Explanatory Variable		**Normative Direction**	**BUY 1.00**	**0.75**	**0.50**	**0.25**	**SELL 0.00**	**Actual Direction**	**Spearman Rank Correlation**	**Wilcoxon Chi-Square** Ho: Best=Worst
RETP6MO	Mean	+	–0.0036	0.0086	–0.0081	–0.0501	–0.0862	+	0.112	30.49
	Median		–0.0275	–0.0117	–0.0047	–0.0406	–0.0762		***	***
	Obs		927	1,083	810	977	960			
VOLP6MO	Mean	–	0.0045	0.0040	0.0041	0.0033	0.0030	+	0.207	140.03
	Median		0.0034	0.0030	0.0030	0.0026	0.0022		***	***
	Obs		935	1,090	812	976	959			
EP	Mean	+	0.0185	0.0260	0.0440	0.0344	0.0233	–	–0.134	51.41
	Median		0.0365	0.0442	0.0531	0.0543	0.0562		***	***
	Obs		982	1,122	816	976	961			
BP	Mean	+	0.3857	0.4422	0.4541	0.5178	0.6325	–	–0.294	310.05
	Median		0.3204	0.3781	0.4085	0.4852	0.6113		***	***
	Obs		982	1,122	815	976	961			
LTG	Mean	–	22.5465	18.3216	14.6492	13.6769	12.0009	+	0.416	401.38
	Median		20.6850	16.1000	12.7500	11.9100	10.4450		***	***
	Obs		712	871	739	856	768			
SGI	Mean	–	1.5133	1.3562	1.2295	1.1704	1.1282	+	0.365	431.40
	Median		1.3280	1.2001	1.1149	1.0967	1.0647		***	***
	Obs		944	1,093	813	962	947			
CFITA	Mean	–	0.1760	0.1383	0.1145	0.0912	0.0801	+	0.253	180.22
	Median		0.1424	0.1089	0.0899	0.0772	0.0623		***	***
	Obs		931	1,010	723	862	850			
TATA	Mean	–	–0.0072	–0.0296	–0.0397	–0.0442	–0.0444	+	0.157	76.20
	Median		–0.0162	–0.0370	–0.0455	–0.0466	–0.0469		***	***
	Obs		783	847	608	732	708			

TABLE 6: Regression of Recommendations on Explanatory Variables

This table reports the result when the level of the analyst recommendation is regressed and various continuous and binary explanatory variables. Panel A reports results for the consensus recommendation. Panel B report results for the individual recommendation (direction and significance of estimated coefficients are unchanged in an Ordered Logit model). The eight investment signals are explained in detail in the Appendix. The binary version of these variables is explained in Table 4. FScore, a composite signal, is also explained in Table 4. ***, **, * signify two-sided statistical significance at 1%, 5%, and 10%, respectively.

PANEL A: Consensus Recommendations ("CONS")

	CONTINUOUS		BINARY		FSCORE	
N	2,916	**R^2** 26.86%	**N**	4,895	**N**	4,895
F-stat	133.4 ***		**F-stat**	143.2 ***	**F-stat**	740.3 ***

VARIABLE	NORM	ACTUAL	$\hat{\beta}$	t	NORM	ACTUAL	$\hat{\beta}$	t	NORM	ACTUAL	$\hat{\beta}$	t
Intercept			3.515	111.55 ***			4.166	243.38 ***			4.239	256.70 ***
RETP6MO	+	+	0.178	5.70 ***	+	+	0.100	7.08 ***				
VOLP6MO	–	+	0.413	0.16 *n.s.*	+	–	–0.074	–5.05 ***				
EP	+	+	0.386	3.83 ***	+	+	0.000	0.03 *n.s.*				
BP	+	–	–0.346	–11.90 ***	+	–	–0.151	–10.21 ***				
SGI	–	+	0.143	6.83 ***	+	–	–0.201	–13.04 ***				
LTG	–	+	0.012	11.81 ***	+	–	–0.175	–10.22 ***				
CFITA	–	+	0.560	8.42 ***	+	–	–0.117	–7.61 ***				
TATA	–	+	0.445	4.20 ***	+	–	–0.087	–5.40 ***				
FSCORE									+	–	–0.106	–27.21 ***

PANEL B: Individual Recommendations ("QREC")

	CONTINUOUS		BINARY		FSCORE	
N	2,916	**R^2** 4.00%	**N**	4,895	**N**	4,895
F-stat	15.15 ***		**F-stat**	14.67 ***	**F-stat**	51.88 ***

VARIABLE	NORM	ACTUAL	$\hat{\beta}$	t	NORM	ACTUAL	$\hat{\beta}$	t	NORM	ACTUAL	$\hat{\beta}$	t
Intercept			0.568	23.80 ***			0.660	56.18 ***			0.679	61.59 ***
RETP6MO	+	+	0.097	4.11 ***	+	+	0.035	3.62 ***				
VOLP6MO	–	–	–2.221	–1.11 *n.s.*	+	–	–0.004	–0.41 *n.s.*				
EP	+	+	0.154	2.01 **	+	+	0.003	0.32 *n.s.*				
BP	+	–	–0.129	–5.85 ***	+	–	–0.057	–5.66 ***				
SGI	–	+	0.053	3.34 ***	+	–	–0.042	–3.94 ***				
LTG	–	+	0.001	1.15 *n.s.*	+	–	–0.018	–1.54 *n.s.*				
CFITA	–	+	0.125	2.49 **	+	–	–0.021	–1.99 **				
TATA	–	–	–0.019	–0.23 *n.s.*	+	+	–0.008	–0.68 *n.s.*				
FSCORE									+	–	–0.019	–7.20 ***

TABLE 7: Regression of Changes in Recommendation on Explanatory Variables

This table reports the result when changes in analyst recommendations are regressed and various continuous and binary explanatory variables, controlling for the prior level of the recommendation. Panel A reports results for changes in the consensus recommendation. Panel B report results for changes in the individual recommendation (direction and significance of estimated coefficients are unchanged in an Ordered Logit model). The eight investment signals are explained in detail in the Appendix. The binary version of these variables is explained in Table 4. FScore, a composite signal, is also explained in Table 4. ***, **, * signify two-sided statistical significance at 1%, 5%, and 10%, respectively.

PANEL A: Change in Consensus Recommendations ("CHGCONS")

	CONTINUOUS		BINARY		FSCORE	
N	2,916	R^2 28.23%	**N**	4,895	**N**	4,895
F-stat	127.2 ***		**F-stat**	193.2 ***	**F-stat**	792.5 ***

VARIABLE	NORM	ACTUAL	$\hat{\beta}$	t	NORM	ACTUAL	$\hat{\beta}$	t	NORM	ACTUAL	$\hat{\beta}$	t
Intercept			0.259	8.90 ***			0.518	23.35 ***			0.530	24.20 ***
Prior Cons Quintile			–0.736	–32.02 ***			–0.805	–40.90 ***			–0.768	–39.62 ***
RETP6MO	+	+	0.176	6.24 ***	+	+	0.068	5.10 ***				
VOLP6MO	–	+	3.455	1.45 *n.s.*	+	–	–0.041	–2.93 ***				
EP	+	+	0.211	2.30 **	+	–	–0.001	–0.10 *n.s.*				
BP	+	–	–0.204	–7.67 ***	+	–	–0.096	–6.85 ***				
SGI	–	+	0.050	2.61 ***	+	–	–0.062	–4.14 ***				
LTG	–	+	0.003	3.26 ***	+	–	–0.090	–5.50 ***				
CFITA	–	+	0.321	5.29 ***	+	–	–0.053	–3.66 ***				
TATA	–	+	0.083	0.86 *n.s.*	+	–	–0.022	–1.44 *n.s.*				
FSCORE									+	–	–0.044	–11.25 ***

PANEL B: Change in Individual Recommendations ("QCHGREC")

	CONTINUOUS		BINARY		FSCORE	
N	2,916	R^2 44.5%	**N**	4,895	**N**	4,895
F-stat	258.7 ***		**F-stat**	405.3 ***	**F-stat**	1795.0 ***

VARIABLE	NORM	ACTUAL	$\hat{\beta}$	t	NORM	ACTUAL	$\hat{\beta}$	t	NORM	ACTUAL	$\hat{\beta}$	t
Intercept			1.045	38.39 ***			1.101	64.43 ***			1.106	66.37 ***
Prior Indiv Quintile			–0.922	–47.48 ***			–0.916	–59.85 ***			–0.905	–59.58 ***
RETP6MO	+	+	0.083	3.28 ***	+	+	0.021	2.06 **				
VOLP6MO	–	–	–2.509	–1.18 *n.s.*	+	–	–0.004	–0.41 *n.s.*				
EP	+	+	0.110	1.36 *n.s.*	+	+	0.005	0.43 *n.s.*				
BP	+	–	–0.120	–5.08 ***	+	–	–0.053	–4.84 ***				
SGI	–	+	0.041	2.42 **	+	–	–0.030	–2.62 ***				
LTG	–	+	0.000	–0.02 *n.s.*	+	–	–0.012	–0.98 *n.s.*				
CFITA	–	+	0.155	2.90 ***	+	–	–0.026	–2.28 **				
TATA	–	+	0.028	0.33 *n.s.*	+	–	–0.003	–0.29 *n.s.*				
FSCORE									+	–	–0.016	–5.59 ***

TABLE 8: Future Returns by FScore and Analyst Recommendation

This table reports the market-adjusted return in the six months following the month of the recommendation. Firms are grouped by their FScore and analyst recommendation. FScore is a composite score based on eight binary investment signals, as explained in Table 4. Panels A and B report results for the level of the consensus and individual recommendations, respectively. Panels C and D report results for changes in these recommendations. ***, **, * indicate two-sided statistical significance at 1%, 5%, and 10%, respectively.

PANEL A: Market-Adjusted Returns, by FScore and Consensus Recommendation Quintile

		Consensus Recommendation Quintile						
Fscore		**Worst = SELL**				**Best = BUY**	**BUY–SELL**	
Group		**0.00**	**0.25**	**0.50**	**0.75**	**1.00**	Excess Return	*t p*
High	Mean Return	0.0170	0.0052	0.0003	0.0345	0.0716	+0.055	*1.78 **
Fscore = 6, 7, 8	Obs	397	280	186	162	82		
Medium	Mean Return	–0.0473	–0.0331	–0.0145	–0.0206	–0.0121	+0.035	*1.80 **
Fscore = 3, 4, 5	Obs	478	559	467	633	497		
Low	Mean Return	–0.1581	–0.1273	–0.0235	–0.0528	–0.0145	+0.144	*3.54 ****
Fscore = 0, 1, 2	Obs	93	148	166	331	416		
High–Low	Excess Return	+0.175	+0.132	+0.024	+0.087	+0.086	**Best, High**	**+0.047** ***
	t	*4.99*	*4.86*	*0.72*	*3.17*	*2.34*	**Worst, Low**	**–0.139** ***
		***	***	*n.s.*	***	***	**Excess**	**+0.186** ***

PANEL B: Market-Adjusted Returns, by FScore and Individual Recommendation

		Individual Recommendation						
Fscore		**Worst = SELL**				**Best = BUY**	**BUY–SELL**	
Group		**0.00**	**0.25**		**0.75**	**1.00**	Excess Return	*t p*
High	Mean Return	–0.0047	0.0094		0.0231	0.0334	+0.026	*1.64 n.s.*
Fscore = 6, 7, 8	Obs	84	427		371	225		
Medium	Mean Return	–0.0562	–0.0439		–0.0215	–0.0023	+0.043	*3.14 ****
Fscore = 3, 4, 5	Obs	114	894		916	710		
Low	Mean Return	–0.1021	–0.0810		–0.0598	–0.0066	+0.076	*2.54 **
Fscore = 0, 1, 2	Obs	26	370		439	319		
High–Low	Excess Return	+0.097	+0.090		+0.083	+0.040	**Best, High**	**+0.027** ***
	t	*1.42*	*3.79*		*3.92*	*1.58*	**Worst, Low**	**–0.082** ***
		n.s.	***		***	*n.s.*	**Excess**	**+0.109** ***

PANEL C: Market-Adjusted Returns, by FScore and Change in Consensus Quintile

		Change in Consensus Quintile						
Fscore		**Worst = DECREASE**				**Best = INCREASE**	**BUY–SELL**	
Group		**0.00**	**0.25**	**0.50**	**0.75**	**1.00**	Excess Return	*t p*
High	Mean Return	0.0153	0.0059	0.0353	0.0107	0.0173	+0.002	*0.09 n.s.*
Fscore = 6, 7, 8	Obs	177	227	269	206	228		
Medium	Mean Return	–0.0571	–0.0215	–0.0300	–0.0144	–0.0082	+0.049	*2.59 ****
Fscore = 3, 4, 5	Obs	486	526	526	508	588		
Low	Mean Return	–0.0475	–0.0660	–0.0885	–0.0398	–0.0254	+0.022	*0.54 n.s.*
Fscore = 0, 1, 2	Obs	250	265	196	209	234		
High–Low	Excess Return	+0.063	+0.072	+0.124	+0.051	+0.043	**Best, High**	**+0.014** *
	t	*1.71*	*2.63*	*5.13*	*1.94*	*1.50*	**Worst, Low**	**–0.057** ***
		*	***	***	*	*n.s.*	**Excess**	**+0.071** ***

PANEL D: Market-Adjusted Returns, by FScore and Change in Individual Recommendation

		Change in Individual Recommendation						
Fscore		**Worst = DECREASE**				**Best = INCREASE**	**BUY–SELL**	
Group		**0.00**	**0.25**	**0.50**	**0.75**	**1.00**	Excess Return	*t p*
High	Mean Return	0.0050		0.0296		0.0252	+0.020	*1.68 **
Fscore = 6, 7, 8	Obs	455		224		428		
Medium	Mean Return	–0.0454		–0.0179		–0.0069	+0.038	*3.28 ****
Fscore = 3, 4, 5	Obs	1,154		398		1,082		
Low	Mean Return	–0.0598		–0.0728		–0.0366	+0.02.3	*0.92 n.s.*
Fscore = 0, 1, 2	Obs	605		130		419		
High–Low	Excess Return	+0.065		+0.102		+0.062	**Best, High**	**+0.025** ***
	t	*3.27*		*3.21*		*3.17*	**Worst, Low**	**–0.060** ***
		***		***		***	**Excess**	**+0.085** ***

TABLE 9: Future Returns, Analyst Recommendations, and Investment Signals

This table reports regressions of market-adjusted return in the six months after the month of the recommendation on various explanatory variables: consensus recommendations measures (Panel A), individual recommendations measures (Panel B), and the FScore, eight binary investment signals, and eight continuous investment signals, as defined in Table 4. For the binary variables, we report the average estimated coefficient and the F-statistic from a test of the null that these variables have no explanatory power. For the continuous explanatory variables, we only report the F-statistic. ***, **, * signify two-sided statistical significance at 1%, 5%, and 10%, respectively.

PANEL A: Consensus Recommendations

Model	*Explanatory variables*	Obs	Consensus (Quintile) [a]	Change in Consensus (Quintile) [a]	FScore[b]	Binary Explanatory Variables[b]	Continuous Explanatory Variables[b]	R^2
1A	*Consensus level*	4,895	0.0257 *t=2.15* **					0.09%
1B	*Consensus level and FScore*	4,895	0.0652 *t=5.10* ***		0.0210 *t=8.27* ***			1.47%
1C	*Consensus level and Binary explanatory variables*	4,895	0.0504 *t=3.83* ***			Avg=0.0243 F^8_{4885}*=12.59* ***		2.11%
1D	*Consensus level and Continuous explanatory variables*	2,916	0.0539 *t=2.94* ***				— F^8_{2906}*=7.17* ***	2.18%
2A	*Change in consensus*	4,895		0.0319 *t=2.66* ***				0.14%
2B	*Change in consensus and FScore*	4,895		0.0280 *t=2.34* **	0.0159 *t=6.72* ***			1.06%
2C	*Change in consensus and Binary explanatory variables*	4,895		0.0287 *t=2.39* **		Avg=0.0209 F^8_{4885}*=11.15* ***		1.93%
2D	*Change in consensus and Continuous explanatory variables*	2,916		0.0281 *t=1.70* *			— F^8_{2906}*=6.64* ***	1.99%
3A	*Consensus and Change in consensus*	4,895	0.0201 *t=1.66* *	0.0279 *t=2.27* **				0.20%
3B	*Consensus, Change in consensus, and FScore*	4,895	0.0615 *t=4.68* ***	0.0144 *t=1.17 n.s.*	0.0206 *t=8.03* ***			1.50%
3C	*Consensus, Change in consensus, and Binary explanatory variables*	4,895	0.0455 *t=3.35* ***	0.0187 *t=1.51 n.s.*		Avg=0.0238 F^8_{4884}*=12.22* ***		2.16%
3D	*Consensus, Change in consensus, and Continuous explanatory variables*	2,916	0.0496 *t=2.65* ***	0.0187 *t=1.11 n.s.*			— F^8_{2905}*=6.83* ***	2.22%

PANEL B: Individual Recommendations

Model	*Explanatory variables*	Obs	Individual Rec'n (Category) [a]	Change in Indiv Rec'n (Category) [a]	FScore[b]	Binary Explanatory Variables[b]	Continuous Explanatory Variables[b]	R^2
1A	*Individual level*	4,895	0.0477 *t=3.69* ***					0.28%
1B	*Individual level and FScore*	4,895	0.0574 *t=4.43* ***		0.0173 *t=7.27* ***			1.34%
1C	*Individual level and Binary explanatory variables*	4,895	0.0511 *t=3.94* ***			Avg=0.0219 F^8_{4885}*=11.56* ***		2.13%
1D	*Individual level and Continuous explanatory variables*	2,916	0.0452 *t=2.63* ***				— F^8_{2906}*=6.73* ***	2.12%
2A	*Change in individual*	4,895		0.0329 *t=3.56* ***				0.26%
2B	*Change in individual and FScore*	4,895		0.0287 *t=3.11* ***	0.0157 *t=6.61* ***			1.14%
2C	*Change in individual and Binary explanatory variables*	4,895		0.0310 *t=3.37* ***		Avg=0.0207 F^8_{4885}*=11.15* ***		2.05%
2D	*Change in individual and Continuous explanatory variables*	2,916		0.0288 *t=2.38* **			— F^8_{2906}*=6.78* ***	2.08%
3A	*Individual and Change in individual*	4,895	0.0313 *t=1.92* *	0.0192 *t=1.65* *				0.33%
3B	*Individual, Change in individual, and FScore*	4,895	0.0527 *t=3.19* ***	0.0053 *t=0.45 n.s.*	0.0171 *t=7.09* ***			1.35%
3C	*Individual, Change in individual, and Binary explanatory variables*	4,895	0.0391 *t=2.34* **	0.0135 *t=1.14 n.s.*		Avg=0.0215 F^8_{4884}*=11.38* ***		2.16%
3D	*Individual, Change in individual, and Continuous explanatory variables*	2,916	0.0324 *t=1.47 n.s.*	0.0145 *t=0.94 n.s.*			— F^8_{2905}*=6.68* ***	2.15%