Analyzing the analysts: When do recommendations add value?

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Abstract

We show that financial analysts from sell-side firms generally recommend "glamour" (i.e., positive momentum, high growth, high volume, and relatively expensive) stocks. Naïve adherence to these recommendations can be costly, because the *level* of the consensus recommendation adds value only among stocks with positive quantitative characteristics (i.e., high value and positive momentum stocks). Among stocks with negative quantitative characteristics, higher consensus recommendations are associated with worse subsequent returns. In contrast, the quarterly *change* in the consensus recommendation is a robust return predictor that appears to contain information orthogonal to a large range of other predictive variables.

1. Introduction

Financial 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]

Analysts gather and process a variety of information about different stocks, form their beliefs about the intrinsic stock values relative to their current market prices, and finally rate the investment potential of each stock. As Elton, Gruber, and Grossman (1986, page 699) observe, 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 unique opportunity to study analyst judgment and preferences across large samples of stocks.

In this study, we investigate analyst preferences across stocks, and evaluate the sources of the investment value provided by analyst stock recommendations and recommendation changes. We expect this research to be of interest to both financial academics and practitioners. From an academic perspective, the study contributes to a better understanding of how analysts evaluate stocks, and their role in the price formation process. From the perspective of investors, this research enhances our understanding of the usefulness (and limitations) of analyst recommendations in investment decisions.

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

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

Finally, from the perspective of sell-side analysts, our study provides a decision aid for making better recommendations (in terms of improved returns prediction).[3]

The first part of the study presents a descriptive profile of the firms preferred by analysts. This research is designed to provide insights on analysts' consistency with various stock characteristics in developing their stock recommendations.[4] The firm characteristics we consider are measures that have a demonstrated ability to forecast cross-sectional returns in prior studies. In the context of this study, these variables serve three purposes. First, they allow us to examine the extent to which the predictive power of stock recommendations is due to analysts' tendency to recommend stocks that appear attractive based on other well-known pricing anomalies.[5] Second, they help us to understand how analyst recommendations are related to "momentum" and "contrarian" investment strategies. Finally, these predictive variables allow us to evaluate the extent to which analysts incorporate concurrently available information in their recommendations.

Our results show that analysts generally prefer "glamour" stocks to "value" stocks. Stocks that receive higher recommendations (as well as more favorable recommendation revisions) tend to have positive momentum (both price and earnings) and high trading volume (as measured by their turnover ratio). They exhibit greater past sales growth, and are expected to grow their earnings faster in the future. These stocks also tend to have higher valuation multiples, more positive accounting accruals, and they invest a greater proportion of their total assets in capital expenditures.

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[3] This statement assumes that analysts are interested in improving the predictive power of their recommendations. As we discuss later, due to incentive issues, optimal returns prediction may not be the primary goal of analysts.

[4] Our approach is similar in spirit to Brunswick's lens model analysis, common in experimental research, in which a decision-maker assesses various information cues to predict a criterion event (e.g., see Libby (1981) for further discussions). Examples of this research related to analysts' stock recommendations include Pankoff and Virgil (1970) and Mear and Firth (1987, 1990); see also Ebert and Kruse (1978).

[5] Prior studies controlled for firm characteristics, such as book-to-market, firm size, and price momentum (e.g., see Womack (1996) and Barber et al. (2001a)). We investigate a much larger set of variables including accounting accruals, capital expenditures, past trading volume, past growth, and forecasted future growth.

However, we show that this preference for growth stocks is not always in line with the interests of the investing public. Specifically, we find that analyst recommendations fail to incorporate the predictive power of most so-called "contrarian" indicators. In the case of seven out of eight contrarian signals, the correlation with analysts' stock recommendations is directionally opposite to the variable's correlation with future returns.

The analysts' penchant for growth firms is consistent with the economic incentives imposed by their operating environment. Most sell-side analysts work for brokerage houses whose primary businesses are investment banking, and sales and trading. Growth firms and firms with higher trading activity make more attractive clients to the brokerage firms. These incentives may cause analysts to, knowingly or otherwise, tilt their attention and stock recommendations in favor of growth and high volume stocks.

We find that, in spite of their general disagreement with the other predictive variables, stocks favorably recommended by the analysts outperform stocks unfavorably recommend by them. This result is consistent with the evidence documented by Barber, Lehavy, McNichols, and Trueman (2001a). However, we find that the *level* of analyst recommendation derives its predictive power largely from a tilt towards high momentum stocks. After controlling for the return predictability of the other signals, we find that the marginal predictive ability of the *level* of analyst recommendation is not significant.

We find that a key reason for the poor performance of the *level* variable is due to analysts' failure to quickly downgrade stocks rejected by the other signals. For stocks where the other signals predict low future returns, favorably recommended stocks significantly *underperform* unfavorably recommended stocks. For this subset of stocks, perhaps favorable analyst recommendations temporarily support prices and delay the eventual incorporation of information in the predictive signals into stock prices. However, within the subset of stocks where other signals predict high future returns, stocks favorably recommended by analysts outperform stocks unfavorably recommended by them.

We also find that *upgraded* stocks outperform *downgraded* stocks, consistent with the findings in Womack (1996). The predictive power of recommendation *changes* (revisions) is more robust than the predictive power of the *level* of analyst recommendations. Specifically, we find that recommendation changes add value to characteristic-based investment strategies that include 12 other predictive variables.

In sum, our results show that analyst recommendations exhibit a style bias in favor of growth over value. That is, they prefer positive momentum stocks with higher growth trajectories that look expensive on most valuation metrics. In the parlance of the behavioral finance literature (e.g., Hong and Stein (1999)), sell-side analysts are better characterized as "trend chasers" than "news watchers." We believe analysts' penchant for growth-style stocks is consistent with their job incentives. Nevertheless, this behavior reduces the effectiveness of their recommendations as a predictor of subsequent returns.

Partly due to this bias, the *level* of analyst recommendation provides little incremental investment value over the other investment signals. However, in spite of a similar bias, recent *changes* in recommendations provide incremental value. This finding suggests that either: (1) sell-side analysts bring information to market through their recommendation changes that is largely orthogonal to the other signals, or, (2) they create their own price momentum by virtue of their stature as "opinion makers." In our concluding section, we discuss implications of these findings for academic research on behavioral finance and financial accounting.

The remainder of the paper is organized as follows. Section 2 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. Sections 4 and 5 evaluate the incremental investment value of recommendations and changes in recommendations. Section 6 summarizes our findings and discusses some of their implications.

2. Analyst recommendations and stock characteristics

This paper provides a link between the literature on analyst recommendations and studies on the predictability of cross-sectional returns. The first part of the study provides a *descriptive* profile of firms that receive stronger recommendations, as well as firms that analysts tend to upgrade (downgrade). This part of our analysis 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 main interest lies in the correlation of these variables with contemporaneous recommendations.

The twelve predictive variables we examine are nominated by prior studies in accounting and finance. We evaluate the predictive ability of analyst recommendations in light of these 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.[6] Barber et al. (2001a) 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 a wide set of investment strategies. We also compare and contrast the predictive ability of consensus recommendation *levels* and *changes*. To our knowledge this is the first study to conduct such a comparison.

2.1 Predictive Variables

We consider twelve 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.

[6] Specifically, Womack (1996) examine new added-to-buy and added-to-sell recommendations, while Elton et al. (1986) examine excess returns in the first calendar month after brokerage recommendation changes.

2.1.1 Momentum and Trading Volume – The first five explanatory variables are based on a stock's recent trading activities and earnings news. Jegadeesh and Titman (1993) show that firms with higher (lower) price momentum earn higher (lower) returns over the next 12 months. We capture the price momentum effect with two variables: **RETP** (**RET2P**) is the cumulative market-adjusted return for each stock in months –6 through –1 (–12 through –7) preceding the month of the recommendation.

Prior studies also show that recent earnings momentum predicts cross-sectional returns (e.g., Chan, Jegadeesh, Lakonishok (1996), Bernard and Thomas (1989)). Specifically, firms with upward revisions in earnings and positive earnings surprises earn higher subsequent returns. We capture the earnings momentum effect with two variables: **FREV** is the analyst earnings forecast revision computed as a rolling sum of over the six months prior to the month of the recommendation, scaled by price. **SUE** is the unexpected earnings for the most recent quarter, scaled by its time-series standard deviation over the eight preceding quarters.

TURN is a measure of the average daily volume turnover for the stock in the six months preceding the month of the recommendation. Lee and Swaminathan (2000) show that high (low) volume stocks exhibit glamour (value) characteristics, and earn lower (higher) returns in subsequent months.[7] They argue that TURN is a contrarian signal, and that high (low) turnover stocks are over-valued (under-valued) by investors.

If analysts based their recommendations on the predictive attributes of price (and earnings) momentum, as well as 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.

[7] As noted in Lee and Swaminathan (2000), trading volume for NASDAQ stocks is inflated by the presence of inter-dealer trades, and is not comparable to the volume reported for stocks traded on the NYSE or AMEX. To adjust for this effect, we compute a percentile rank score by exchange.

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 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 Firm Size – Fama and French (1992), among others, show that small firms have generally earned higher returns than large firms. While opinions differ on the robustness of the result and the interpretation of this variable, we include a control for firm size. Specifically, we compute **SIZE** as the natural log of a firm's market capitalization at the end of its most recent fiscal quarter.

2.1.5 Fundamental Indicators – Finally, we include two fundamental indicators from the accounting literature: **TA** (total accruals divided by total assets) and **CAPEX** (capital

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[8] See, for example, the discussions in Fama and French (1992) and Lakonishok et al. (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.

expenditures divided by total assets). TA provides a measure of the quality of earnings, and could signal earnings manipulation. For example, if firms excessively capitalize overheads into inventories, or if they fail to write off inventories in a timely manner, then the inventory component of accruals will rise. Such accounting gimmicks lead to positive accruals. Sloan (1996) finds that firms with low accruals (more negative TA) earn higher future returns than firms with high accruals. 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.

However, Chan, Chan, Jegadeesh and Lakonishok (2001) point out that firms with large sales growth will experience large increases in accounts receivables and inventory, mainly to support the increased levels of sales. In fact, Chan et al. (2001) find that the decile of firms with the largest accruals experience sales growth of 22% per year over the prior three year period compared to 7% per year sales growth for the decile of low accrual firms. They also find large earnings growth for high accrual firms. Therefore, accruals may be symptoms of managerial manipulation in some instances, but high accruals are also associated with strong past operating performance.

Beneish, Lee, and Tarpley (2001) show that growth firms with high CAPEX also tend to earn lower returns. Such firms are over represented in the population of extreme losers (so called "torpedoed" stocks). They argue that high CAPEX firms are growth firms that tend to over-extend themselves. Again, if analysts pay attention to these results, lower TA (and lower CAPEX) firms should receive more favorable recommendations.

To summarize, all twelve variables we use have demonstrated an ability to predict cross-sectional returns in prior studies. While not an exhaustive list, these variables do capture much of what 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 all the stocks in the Zacks Investment Research recommendations database for the period 1985 through 1998.[10] Zacks collects the recommendations from contributors and assigns standardized numerical ratings (1=strong buy, 3=hold, 5=strong sell). 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, 3=hold, 1=strong sell).

For each firm, we calculate the *consensus recommendation level* (**CONS**) and the *consensus recommendation change* (**CHGCONS**) at the end of each calendar quarter. The *consensus recommendation level* is the mean of all outstanding recommendations for a given firm, issued a minimum of two days and a maximum of 12 months prior to the calendar quarter end. We only use the most recent recommendation for a given analyst. The *consensus recommendation change* is the increase (or decrease) in the consensus recommendation level, from the end of the prior calendar quarter to the end of the current calendar quarter.

For each observation, we require that the firm's market price information be available in the CRSP database, that its earnings forecasts be available in the I/B/E/S database, and that its accounting information be available on the merged quarterly COMPUSTAT database. These data constraints ensure the availability of basic financial information for each firm in our sample. A firm-quarter observation is included in our final sample only if all twelve of the investment signals (previously discussed, and described in detail in the Appendix) are available for that quarter.

[10] Zacks obtains the recommendations from written reports provided by brokerage firms and uses the date of the recommendation as the date of the brokerage firm report. The academic database from Zacks does not include recommendations from several large brokerage houses, most notably Merrill Lynch, Goldman Sachs, and Donaldson, Lufkin, and Jenrette.

Figure 1 illustrates the data collection periods for each of our empirical measures. For a consensus recommendation level observed at the end of quarter *t*, we use market-related data (past returns, and trading volume) and analyst-related data that are collected up to 12 months prior to the end of quarter *t*. For accounting-related data, we identify the most recent quarter for which an earnings announcement was made at least two months prior to the end of quarter *t*, and calculate the accounting data based on the rolling-sum of this and the three prior quarters. Subsequent return accumulation begins with the first trading day of quarter *t+1*.

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, and (3) future returns reflect potentially tradable strategies.

3.2 Data Description

Our data collection procedure yielded an average of 971.4 firm-observations per quarter over the 56 quarters. Table 1 provides descriptive statistics on the number of observations by year (Panel A), by exchange (Panel B), and by NYSE size decile (Panel C). Panel A shows that the average number of firm-observations has increased over time from 1985 through 1998. Panel B shows that approximately 56% (44%) of our observations consists of NASDAQ (NYSE/AMEX) firms. Finally, Panel C shows these observations are evenly distributed across the NYSE size deciles, but that size varies by exchange. Additional analyses (not reported) show that these firms span a large number of different industries, with no single industry representing more than 8.1% of the total sample.

Table 2 reports information on the distribution of the consensus recommendation levels and changes. Recall that, 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). For both the consensus recommendation levels and changes, we also group the firm-observations into quintiles, calculated separately for each quarter. The quintiles are labeled 0.00, 0.25, and so on to 1.00, where

0.00 contains the quintile of firms with the least favorable ratings and 1.00 contains the quintile of firms with the most favorable ratings. In the case of recommendation changes, all "no change" observations are included in the middle change quintile.

Panel A of table 2 reports descriptive statistics for five consensus recommendation *level* quintiles, calculated separately for each of the 56 quarters (1.00=strong buy, 0.50=hold, 0.00=strong sell). It is clear from these results that analysts rarely issue sell or strong-sell recommendations. The mean consensus recommendation level in the bottom consensus level quintile is only a hold (2.76).[11]

Panel B reports the *change* in analyst recommendations, defined as the current quarter recommendation level minus the prior quarter recommendation level. Quintiles are calculated separately for each of the 55 quarters (1.00=strong increase, 0.50=hold, 0.00=strong decrease), but with all "no change" observations included in the middle quintile. In our sample, analysts were slightly more likely to downgrade a firm than upgrade it (mean change = –0.01).

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, 32.2% of the firms in the top quintile in terms of the prior consensus appear in the bottom quintile in terms of *changes* in the consensus recommendation. Conversely, 29.0% of the firms in the bottom quintile of prior consensus recommendations appear in the top *changes* quintile. In subsequent tests, we control for this strong negative correlation.

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[11] Commercial services that report analyst recommendations (e.g., Zacks, 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 level in our sample is equivalent to a rating of 2.33 (6.00 - 3.67) in Zacks. The mean consensus in the bottom levels quintile is equivalent to a Zacks rating of 3.24 (6.00 – 2.76).

4. Empirical Results

4.1 Analyst Recommendations and Future Returns

Table 3 provides evidence on the predictive ability of analyst stock recommendations. For this table, we only report results for a six-month holding period. Panel A reports the Spearman rank correlation between the two recommendation measures and market-adjusted returns for the six months following the month of recommendation. These correlations are computed each quarter. Table values represent the mean and median correlations over 56 quarters for levels and 55 quarters for changes. The Mean results are based on two-sided T-tests with Hansen-Hodrick autocorrelation adjusted statistics; the Median results are based on two-sided Wilcoxon signed-rank tests. The table reports the correlation for the continuous variables, as well as the categorical variables based on quintile assignments as defined in Table 2.

Table 3 confirms prior studies in that both CONS and CHGCONS are correlated with future returns. Specifically, firms that receive more favorable recommendations (buys or upgrades) earn higher subsequent returns than firms that receive less favorable recommendations (sells/holds or downgrades). Recall that our recommendation variables are based on month-end information. Therefore, these results likely under-estimate the predictive power of analyst recommendations, as much of the associated price adjustment takes place in the first 2-3 weeks after the news release.[12]

The next two panels report the mean and median market-adjusted return in quintile portfolios sorted each quarter by CONS, the analyst recommendation *level* (Panel B), and by CHGCONS, the *change* in analyst recommendation (Panel C). Table values represent the mean market-adjusted returns for each quintile portfolio. For CONS, the mean difference between top and bottom quintile is 2.3% over the next six months. For the

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[12] Our results are similar in magnitude to Womack (1996), who examined individual recommendations (specifically, he examines new buy or new sell recommendations). Compared to his study, we probably understate total returns because our holding period does not begin until the beginning of the next calendar month. Barber et al. (2001a) and Elton et al. (1986) test somewhat different implicit strategies, making direct comparisons more difficult.

CHGCONS, top and bottom groups differed on average by around 2.7% over the next six months.

4.2 Other Investment Strategies

Table 4 reports the Spearman rank correlation between future returns and other investment strategies. Over our sample period, most of these variables are correlated with future returns in the direction reported in prior studies. The two exceptions are SIZE and BP. In the 1985-1998 period, large firms outperformed small firms on a market-adjusted basis while the evidence documented by Banz (1981) indicates a negative relation between size and returns in the pre-1980 period. Also, Fama and French (1992) and others have found a negative positive relation between BP and future returns. But in our sample period, value firms did not outperform growth firms. In fact, there is negative correlation between BP and future returns, although this correlation is not statistically significant. We also find a statistically insignificant negative correlation between LTG and future returns, while Lakonishok et al (1994) report significantly negative correlation.

In general, firms with positive price momentum (RETP and RET2P), positive earning momentum (FREV and SUE), and low trading volume (TURN) earned higher market-adjusted returns over the next six months. Similarly, low SG firms, low TA and CAPEX firms, as well as high EP firms, earned higher subsequent returns. Aside from firm size, the highest absolute correlations are observed for earnings forecast revisions (FREV), price momentum (RETP), and total accruals (TA). These correlation levels range from +0.099 (FREV) to -0.081 (TA).

To assess the aggregated effect of combining these signals, we compute three simple summary quantitative measures (**Qscore**, **Momentum**, and **Contrarian**). To construct these variables, we first convert each of the 12 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 its median value in a given quarter, and 0 otherwise. We compute the **Qscore** for each stock by aggregating its 12 binary signals. This aggregation process gives us a measure that captures how these signals work together in quantitative investment strategies. We chose this simple measure rather than conduct a search for a more efficient return predictor because it is not our goal to create an optimal measure to predict future returns.

We also separately compute a M**omentum** score by aggregating the binary scores across the momentum signals RETP, RET2P, FREV, and SUE. We aggregate the remaining scores across the remaining signals to obtain the **Contrarian** score. We label these signals as contrarian because typically when these signals are associated with high future growth in earnings or sales, they tend to be associated with low future returns.

Under the column heading "% Positive", Table 4 reports the percent of total observations that received a value of "1" for each investment signal. Under the column heading "Correlation", we report the Spearman rank correlation of these binary variables with future returns. As expected, correlation levels are slightly lower when we move from the continuous variable to this binary coding. However, the binary versions of most variables still exhibit statistically significant correlations with future returns. The "Mean net portfolio return" is the mean difference in returns between the portfolio of top firms (with binary variable equal to 1) and the portfolio of bottom firms (with binary variable equal to 0). The final column in this table indicates the percentage of the 56 quarters in which the net portfolio return was above 0%.

Table 5 examines the correlation between three summary quantitative variables and future returns, defined as the market-adjusted return over the next six months. The three summary variables are: **Momentum** (the sum of the four momentum signals: RETP, RET2P, FREV, and SUE), **Contrarian** (the sum of the remaining eight signals), and **QScore** (the sum of all twelve binary signals). Panel A reports the Spearman rank correlation between each summary measure and future returns. We report results for both a continuous measure and a quintile measure of the summary variable (see Table 2). Panel B reports future returns grouped by QScore quintiles, Panel C reports future returns grouped by Momentum quintiles, and Panel D reports future returns for firms grouped by Contrarian quintiles.

Panel A shows that all three summary variables are positively correlated with future returns. QScore has the highest mean Spearman rank correlation (0.125), but both Momentum and Contrarian are positively correlated with future returns (approximately 0.09). Panel B shows that the mean (median) difference between top and bottom QScore quintile returns is 5.71% (7.70%). The mean (median) difference for the Momentum ranking (Panel C) is approximately equal, at 5.73% (6.20%). The mean (median) return difference between the extreme Contrarian quintiles (Panel D) is 3.64% (7.86%). For all three variables, the mean and median returns decline monotonically as we move down the five quintiles. Clearly, these summary variables are correlated with future returns during our sample period.

4.3 Analyst Recommendations and Investment Strategies

Thus far, we have established the predictive ability of the investment signals in our sample. We have also documented the predictive ability of the analyst stock recommendations. In this section, we examine the relation between analyst recommendations and various investment signals.

Table 6 reports the mean and median value of each of the 12 investment signals by consensus recommendation quintile. Under the heading "Normative Direction," we show the direction of correlation between each variable and future market-adjusted return as indicated by prior research. Under the heading "Actual Direction" we report the direction of correlation between that variable and the analysts' consensus recommendation in our sample. We also report the Spearman rank correlation between each variable and the consensus recommendation. In addition, we provide T-tests of the null that the mean value is the same for the top and bottom consensus recommendation quintiles.

Table 6 shows that analysts' consensus recommendations correspond well with the Momentum indicators. Specifically, analysts exhibit a strong preference for positive momentum stocks. In fact, the Spearman rank correlation between analyst recommendations and the four momentum variables range from 26.9% to 34.6%. In particular, analysts seem to recommend most strongly firms with recent upward earnings forecast revisions (FREV) and positive earnings surprises (SUE).

But perhaps the most striking result in Table 6 is the consistency with which analyst stock recommendations contradict the expected normative usage of the Contrarian 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 (TURN) over stocks with low turnover. They also prefer large SIZE, low BP, high SG, high LTG, high TA, and high CAPEX stocks. In fact, the only contrarian variable that analysts seem to get "right" is EP – they prefer stocks that have higher earnings-to-price ratios to stocks that have lower earnings-to-price ratios.[13]

Table 7 provides additional evidence in a multivariate setting. This table reports results when each recommendation variable is regressed on the 12 explanatory variables. Panel A (B) reports results when the dependent variable is the *level of (change in)* the consensus recommendation. With few exceptions, Table 7 confirms the univariate results reported in Table 6. Panel A shows that, with the exception of BP, the level of the consensus recommendation continues to run counter to the Contrarian variables. Panel B shows that changes in the consensus recommendation are also consistent with the Momentum variables, and counter to the Contrarian variables. In other words, analysts tend to revise their recommendations upwards (downwards) for positive (negative) momentum stocks. However, they also tend to revise their recommendation upwards for high TURN, high LTG, high SG, and high CAPEX firms.

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[13] Bradshaw (2000) shows that analyst recommendations are correlated with a firm's PEG ratio. Our results contain both components of the PEG ratio (the P/E ratio and the forecasted earnings growth). These findings are consistent, because even in our sample, analysts exhibit a strong preference for high LTG firms (Spearman rank correlation of 27.2%).

An interesting exception is the total accruals variable (TA). While the level of the consensus recommendation is positively correlated with TA, the change in the consensus appears is negatively correlated with TA. These results suggest that analysts revise their recommendations in a manner consistent with the information content of accruals. In other words, while mean recommendation levels favor firms with income increasing accruals, when analysts revise their recommendations, firms with income decreasing (income increasing) accruals tend to receive upward (downward) revisions. The implication is that analysts do not initially pay sufficient attention to the quality of earnings as revealed by TA, but they adjust in the right direction over time.

The general picture that emerges from the analysis is that analysts favorably recommend stocks with strong past operating performance and stocks that are expected to deliver healthy improvements in operating performance in the future. High SUE for the most favorably recommended stocks indicates that these stocks had strong operating performance in the past. Large FREV indicate that analysts have favorably revised their expectations about the future operating performance of these stocks. In the same spirit, high recent returns capture favorable revisions in market expectations about future operating performance.

The contrarian signals that analysts prefer also suggest that they pick stocks with strong operating performance. For example, analysts prefer low BP firms and high TA firms. Low BP firms generally have higher returns-on-equity (ROE), and are expected to enjoy faster growth in profitability in the future. Similarly, high TA firms on average have faster sales growth than low TA firms (see Chan et al. 2000). Historically, however, the contrarian characteristics that analysts prefer (with the exception of EP) are associated with lower future returns. These findings indicate that when there is a conflict between indicators of strong operating performance, and the large sample empirical relation between the signals and future returns, analysts tend to make their recommendations on the basis of strong past operating performance.

In sum, these findings show that the momentum signals preferred by analysts will help in the performance of their recommendations, but their contrarian signal preferences will likely hurt their performance. In the next section, we evaluate the predictive power of analyst recommendations in conjunction with the other twelve signals.

5. Incremental Value of Analyst Recommendations

In this section, we evaluate the incremental value of analyst recommendations, and changes in these recommendations, when these signals are used in conjunction with other predictive signals.

5.1 Multivariate Analysis

We first examine the relation between future returns and QCON and QCHGCON. As a starting point, we define future returns as the market–adjusted return in the six months after the month of the recommendation (RETF). Table 8 reports the regression coefficients averaged across the quarters in the sample. Because RETF overlaps across quarters, we use autocorrelation-consistent standard errors to compute the t-statistic.[14] Model A1 in Panel A is a univariate regression, with RETF as the dependent variable and QCON as the independent variables each quarter. The results show that the coefficient on QCON is positive and statistically significant in this regression, indicating that when used alone, it helps predict future returns.

To assess whether QCON incrementally predicts returns when used in conjunction with the 12 characteristic-based signals, we consider three different regression specifications. In the first multivariate regression, we use the QCON and Qscore as independent variables (Model A2). These results show that QCON loses its statistical significant once QScore is introduced.

[14] Since the return overlap is over one quarter, we allow for the first-order serial correlation to be different from zero while computing the autocorrelation-consistent standard errors.

Next, we consider a regression model where we use QCON and the 12 signals as separate independent variables (Model A3). This specification pits each of these signals against QCON individually rather than at an aggregated level. With the exception of BP and SIZE, the other investment signals are all correlated with future returns in the expected direction. However, only RETP, FREV, TA, and CAPEX, are individually significant. QCON is not significant in this regression.

Collectively, the evidence from Model A2 and Model A3 suggests that while QCONS is weakly correlated with returns, its contribution is minor when considered in conjunction with the other signals. However, these models may be somewhat handicapped against QCON because they allow the slope coefficients for the independent variables to take the ``right'' sign in predicting returns. In most instances, the binary contrarian signals are negatively correlated with QCON but they are positively correlated with future returns.

As a final test, we fit a regression where the independent variable that we use in addition to QCON is and its fitted value (Qfitcon) from the regression in Table 7, Panel A (Model A4). Interestingly, QCON is not statistically significant in this regression, but Qfitcon is significant. This evidence indicates that the investment value of QCON is largely due to its tilt towards firm characteristics that are related to future returns.

Table 8, Panel B reports the results for regressions with QCHGCONS. Model B1 shows that QCHGCONS is able to predict future returns. The estimated coefficient (2.25%) can be interpreted as the hedge return between the extreme CHGCONS quintiles over the next six months. Notice that the estimated coefficient and the *t*-statistic on QCHGCONS both decrease as we introduce QScore and the other control variables (Models B2 to B3). In the last regression specification (Model B4), we include the fitted value (Qfitchgcon) for QCHGCON from the regression in Table 7, as well as QCHGCON, in the regression. Model B3 shows that this variable remains statistically significant in the presence of all 12 other investment signals. Model B4 shows that it is significant even with the inclusion of Qfitchgcon. This evidence shows that QCHGCONS is incrementally useful in predicting returns. In fact, in Models B3 and B4, it is the explanatory variable associated with the highest *t*-statistic.[15]

5.2 Two-way analysis

Although analyst recommendations do not add value to the general population of stocks when used in conjunction with other characteristics, it is possible that they may add incremental value for subsets of stocks. In this subsection, we examine the performance of analyst recommendations and recommendation changes within quintiles of stocks ranked partitioned based on the summary scores.

Table 9 reports results of a two-way analysis, in which firms are sorted by their quantitative summary score (QScore), as well as by their analyst recommendation (CONS or CHGCONS). Panel A of this table reports results for the *level* of the consensus recommendation (CONS). Panel B reports results for individual recommendations (CHGCONS). Panel C reports results for a combined strategy involving both level and change quintiles. For this panel, Worst (Best) firms are firms that are in both the lowest (highest) CONS and the lowest (highest) CHGCONS quintile. All other firms are assigned to a middle category.

Panel A reports six month market-adjusted returns of firms sorted by CONS and QScore. Looking along the bottom row of each panel, it is clear that the QScore variable has significant predictive power for returns after controlling for the analyst recommendation. High QScore firms earn significantly higher subsequent returns in all analyst recommendation categories. QScore performs particularly well among firms with the highest analyst recommendation. In that category, the return difference between top and bottom QScore firms is 9.10% over the next six months.

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[15] The holding period for the strategies tested in our paper includes the year 1999, but not 2000. Barber et al. (2001b) report that during the calendar year 2000, stocks least favorably recommended by analysts earned higher subsequent returns than stocks that are highly recommended. However, their tests only examine the *level* of the consensus variable, which has marginal predictive power even during our sample period.

The results along the right column of each panel show that analyst recommendations (CONS) have some limited predictive power after controlling for QScore, but this power is conditional on the QScore quintile. Specifically, CONS is only useful among high QScore firms. In the highest QScore quintile, top CONS quintile firms earn 3.24% more than bottom CONS quintile firms over the next six months. However, for firms with a low QScore, the return to a CONS strategy is negative. This result suggests that among low QScore stocks, firms more highly recommended by the analysts actually do worse in the future than firms with low recommendations.

Another result that emerges from this table is that when analyst recommendations and the QScore signal disagree, the QScore signal tends to dominate. The cells along the off diagonal of each panel (toward the lower-left and upper-right corners) report mean returns when the QScore and the analyst recommendation signals are in disagreement. In Panel A, firms in the lower-left corner (High QScore firms with low recommendations) earn higher average returns than firms in the upper-right corner (Low QScore firms with high recommendations). The return difference of 5.86% (labeled "DISAGREE") is statistically significant at the 1% level. Evidently, when the two signals conflict, the QScore results in more reliable returns predictions.

Finally, when the two signals agree, we find the highest predictive power for returns. In the lower-right corner of each panel, labeled "AGREE", we report the return differential when analyst recommendations are combined with the QScore indicator. These cells show the mean return differential between firms with the best recommendations and highest QScores (Best-and-High), and firms with the worst recommendations and lowest QScores (Worst-and-Low). In all three panels, the Best-and-High group earns higher returns than the Worst-and-Low group. The returns differential ranges from 7.03% to 9.35% over the next six months, which is greater than returns earned by considering either signal alone.

Figure 2 depicts the cumulative excess return from various hedge strategies involving both analyst recommendations and the QScore. The results for the six-month holding period are the same as those reported in Table 9, but Figure 2 extends Table 9 by reporting the cumulative excess return over different holding periods (1, 3, 6, 9 and 12 months). Each graph reports the returns to three strategies. The High-Low strategy involves taking an equal-weighted long position in the top QScore quintile firms and short selling an equal-weighted position in the bottom QScore 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.

As indicated by Panel A, the level of the consensus recommendation (CONS) has limited ability to predict returns. The hedge return to the ANALYST variable in this graph never exceeds 2.2% (at the six month horizon). When used in combination with QScore, this variable adds a modest 1.5% to the mean QScore strategy's return over six months. Panels B shows that portfolios formed on the basis of the change in the consensus recommendation (CHGCONS) performs somewhat better. When CHGCONS is used alone, the Increase-Decrease hedge strategy based on top and bottom quintiles generates 2.7% over six months, and 3.6% over 12 months. When combined with QScore, this variable adds approximately 2% to the QScore strategy returns over six months.

Panel C reports the results when both CONS and CHGCONS are used. As indicated in Table 9, this double filter results in fewer positions being taken (an average of 13.3 buys and 24.3 shorts per month). At the same time, the cumulative excess return based on the analyst variable alone increases to 5.3% over six months. When used it combination with QScore, this combined strategy adds almost 4% to the excess return of the QScore strategy over six months. These results suggest that the two analyst recommendation measures are not redundant for returns prediction.

Table 10 provides a more comprehensive analysis of the cumulative excess returns to analyst recommendation strategies over various holding periods. To construct this table, firms are grouped each quarter into quintiles by their quantitative score (QScore, Momentum, and Contrarian), as well as consensus recommendation (either CONS or

CHGCONS). Panel A reports the mean difference in market-adjusted returns between the extreme CONS quintiles (BUY-SELL) within each quantitative measure quintile over 55 quarters. Panel B repeats the analysis for CHGCONS. We report the cumulative excess return for 1, 3, 6, 9, and 12 month holding periods for each strategy. Positive (negative) table values indicate that the strategy generated mean favorable (unfavorable) excess returns over the holding period.

Several facts emerge from this table. First, as we have seen earlier, CHGCONS is a better predictor of returns than CONS. Panel B shows that CHGCONS strategies generate positive returns over all holding periods and in all quintiles formed on QScore, Momentum, and Contrarian. In contrast, a strategy based on CONS is far less consistent. Panel A shows that, controlling for QScore, a CONS based strategy is almost as likely to yield negative excess returns as positive excess returns.

Second, analysts are more likely to add value to contrarian investing strategies. In both panels, the analysts seem to better compliment the Contrarian strategy than the Momentum strategy. This result perhaps is not surprising, because we have seen earlier that some of the analyst's predictive power derives from their tendency to select positive momentum stocks.

Third, Table 10 shows that the main reason the CONS strategy is less reliable is because it generates positive excess returns only in high QScore quintiles. In low QScore quintiles, the excess returns to a CONS based strategy are reliably negative. In other words, when selecting among firms with unfavorable quantitative signals, it is better to invest *against* analyst recommendations than to invest according to these recommendations. This result is quite striking and is stronger as the holding period lengthens. Moreover, it is observed within both Momentum quintile partitions and Contrarian quintile partitions.

Figure 3 provides a graphic illustration of the different roles played by CONS and CHGCONS in return prediction. These figures show the difference in mean returns between the extreme recommendation quintiles across the quintiles of each quantitative investment signal. Across the bottom of each figure is the holding period of the strategy. The darker bars correspond to low quintiles by each summary quantitative score (QScore, Momentum, and Contrarian), the lighter bars correspond to high quintiles.

Panel A shows that the CONS strategy yields positive returns for high QScore quintiles (lighter bars), but the same strategy yields negative returns for low QScore quintiles (darker bars). Apparently the level of the consensus recommendation (CONS) is a favorable indicator of future returns only when a firm is in the higher QScore (or higher Momentum, higher Contrarian) quintiles. In other words, analysts seem to be able to further identify the superior firms among a set of firms that already have favorable fundamental or operating characteristics. However, when a firm is in the lower Momentum or Contrarian quintiles, analyst recommendations operate in the wrong direction, and it would be unwise to follow their stock picks. In fact, when a firm has unfavorable fundamental or operating characteristics, it is better to trade *against* the consensus analyst recommendations.

Panel B shows that the same pattern does not appear for CHGCONS. In all sub-portfolios and over all holding periods, this strategy results in positive excess returns. In other words, the analysts revise their recommendations in a manner that is consistent with subsequent returns. However, the level of their consensus recommendation is only a useful return predictor when it is confirming the quantitative investment signals.

In sum, Tables 8 through 10 show that the predictive power of analyst stock recommendations derives largely from their correlation with the other explanatory variables. The usefulness of the consensus level measure (QCON) is conditional on the quantitative investment signal. Specifically, QCON is a useful predictor of returns only when it serves to confirm favorable quantitative signals. The incremental usefulness for returns prediction is most pronounced for the change of the consensus recommendation (QCHGCON).

6. 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. We focus on variables that prior studies show have some predictive power for future returns, and critically evaluate the investment value of these recommendations in light of the other signals.

We find that analysts prefer growth stocks that appear over-valued by traditional measures. On further analysis, we find that analyst recommendations are positively correlated with momentum indicators but negatively correlated with contrarian indicators. 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 the parlance of Hong and Stein (1999), financial analysts appear to be “trend chasers” rather than fundamental “news watchers.”

We find that the level of the consensus analyst recommendation does not contain incremental information for the general population of stocks when it is used in conjunction with other predictive signals. For the subset of firms with favorable momentum and contrarian signals, we find that firms favored by analysts tend to outperform firms that are less favored. However, for the subset with less favorable quantitative signals, the stocks that analysts recommended most favorably by analysts actually *underperform* the stocks that they recommend less favorably. Perhaps, for this subset of firms, favorable analyst recommendations actually help delay the eventual convergence of price to the underlying fundamentals.

The explanatory power of the *change* in the consensus analyst recommendation is more robust than that of the *level* of the recommendation. Changes in recommendations over the prior quarter predict future returns when used separately and when used in conjunction with other predictive signals. These findings suggest that the return-relevant information contained in analyst recommendation changes is, to a large extent, orthogonal to the information contained in the other variables.

One interpretation of our finding is that recommendation changes 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. Since we do not control for industry-related effects, it is possible that analyst recommendation revisions reflect news about a firm's competitive position in its industry. The evidence is at least consistent with the analysts' claim that they bring some new information to market. Our findings show this information is better reflected through changes in their recommendation than through its absolute level.

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 (Logue (1986)). 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 ratios, lower LTG and SG measures, more negative (income decreasing) accruals, and lower capital expenditures.[16]

From an investment perspective, our results suggest analyst recommendations play a dual role in the price formation process. On the one hand, analysts seem over-enamored with growth and glamour stocks. To the extent that their opinion affects public sentiment, this evidence is consistent with the view that they contribute to noise trading in the market. On the other hand, these findings suggest analyst recommendations can still play a useful role in investment strategies. When analyst recommendations conflict with a combined investment signal (the QScore), the QScore dominates. However, within individual QScore categories, analyst recommendations can be incrementally useful in returns prediction. The change in the consensus recommendation, in particular, has significant ability to forecast near-term (3 to 12 month) cross-sectional returns.

In contemplating its usage in investment strategies, readers need to consider several factors. First, transaction costs issues are not explored in this study. Second, 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 12 control variables known to be associated with expected returns. Nevertheless, the possibility cannot be ruled out. Finally, we show that in some circumstances (i.e., among firms with poor quantitative scores), it is dangerous to follow analyst recommendations. Consistent with the claim of some pundits (e.g., Der Hovanesian (2001)), the level of the analyst recommendation itself can sometimes be a contrarian signal.

Our results suggest that fundamental analysts and investment houses that employ large-sample quantitative techniques could each learn something from the other. Behavioral

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[16] This assumes that our results are not due to incentive issues. 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 analysts' recommendations may also be hindered by psychological factors, such as analysts' relative confidence in their own judgments (Nelson, Krische, and Bloomfield (2000)).

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 should pay more attention to the results of large-sample studies. On the other hand, quantitative investors could also benefit by augmenting their stock selection process with the consensus recommendation of sell-side analysts.

Finally, we believe these results also have implications for studies in behavioral finance. One of the major challenges confronting this emerging literature is the identification of factors that drive investor (or noise trader) sentiment. Black (1986, page 531) defines noise trading as " trading on noise as if it were information." Shiller (1984) argues that investor sentiments arise when investors trade on pseudo-signals, such as the forecasts of Wall Street gurus. Our results suggest that the preferences of sell-side analysts could play a role in explaining a particular type of noise trading.

Specifically, we find that sell-side analysts (and those who follow their recommendations) are over-enamored with high-volume, high-multiple, stocks. Lee and Swaminathan (2000) characterize these stocks as "late-stage" momentum plays, and show that they are particularly susceptible to subsequent price reversals. In the same spirit, Hong and Stein (1999) argue that traders investing in late-stage momentum stocks impose an externality on other traders by "piling on" in stocks that have already moved too far from their fundamental value. This behavior leads to negative serial correlation in returns over the long horizon, as prices eventually correct. Using analysts' expressed preferences, as revealed in their stock recommendations, we begin to put a face on the stocks preferred by these noise traders.

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APPENDIX: Investment Signals

This appendix provides a detailed description of the twelve investment signals used in the study. All these explanatory variables were windsored at the 2½ and 97½ percentiles within each quarter. [*text*] refers to the data source, where D# is the item number from Quarterly Compustat. For ease of exposition, firm-specific subscripts have been omitted. In all cases, the related consensus recommendation levels and changes are collected at the end of quarter t, which has month-end m. q denotes the most recent quarter for which an earnings announcement was made. We require the announcement to be made at least two months prior to the end of quarter t, and that $q \geq t-4$.

Variable	Description	Calculation Detail *[Source]*
1. RETP	Cumulative market-adjusted return for the preceding six months (months –6 through –1)	$\{[\Pi_{i=m-6}^{m-1}(1+\text{monthly return}_i)]-1\}$ $-\{[\Pi_{i=m-6}^{m-1}(1+\text{value-weighted market monthly return}_i)]-1\}$, where m = month-end of quarter t *[CRSP]*
2. RET2P	Cumulative market-adjusted return for the second preceding six months (months –12 through –7)	$\{[\Pi_{i=m-12}^{m-7}(1+\text{monthly return}_i)]-1\}$ $-\{[\Pi_{i=m-12}^{m-7}(1+\text{value-weighted market monthly return}_i)]-1\}$, where m = month-end of quarter t *[CRSP]*
3. TURN	Average daily volume turnover	Percentile rank $\left[\frac{\sum_{i=1}^{n}\text{Daily volume}/\text{Shares Outstanding}}{n}\right]$, by exchange, where n = number of days available for 6 months preceding the end of quarter t (months m-6 though m-1) *[CRSP]*
4. SIZE	Market cap (natural log)	$Size_t = LN\ (P_{,t} * Shares\ Outstanding_t)$ = LN (price at the end of the quarter t *[D14]*, multiplied by common shares outstanding at the end of quarter t [*D61*])
5. FREV	Analyst earnings forecast revisions to price	$\sum_{i=0}^{5}\left(\frac{f_{m-i}-f_{m-1-i}}{P_{m-1-i}}\right)$, where f_m = mean consensus analyst FY1 forecast at month m, the month-end of quarter t *[IBES]* P_{m-1} = price at the end of month m-1, relative to the month-end of quarter t *[CRSP]* Thus, $\sum_{i=0}^{5}\left(\frac{f_{m-i}-f_{m-1-i}}{P_{m-1-i}}\right)$= rolling sum of preceding six months revisions to price ratios
6. LTG	Long-term growth forecast	Mean consensus long-term growth forecast at end of quarter t [*IBES*]
7. SUE	Standardized unexpected earnings	$\frac{(EPS_q\text{-}EPS_{q-4})}{s_q}$, where q = most recent quarter for which an earnings announcement was made a minimum two months prior to the end of quarter t, with $q \geq t$-4 $EPS_q - EPS_{q-4}$ = unexpected earnings for quarter q, with EPS defined as earnings per share (diluted) excluding extraordinary items *[D9]*, adjusted for stock distributions *[D17]* s_q = standard deviation of unexpected earnings over eight preceding quarters (quarters q-7 though q)

APPENDIX: Investment Signals (Continued)

Variable	Description	Calculation Detail *[Source]*
8. SG	Sales growth	$\frac{\sum_{i=0}^{3} Sales_{q-i}\ [D2]}{\sum_{i=0}^{3} Sales_{q-4-i}\ [D2]}$, where q = most recent quarter for which an earnings announcement was made a minimum two months prior to the end of quarter t, with $q \geq t\text{-}4$ Thus, $\sum_{i=0}^{3} Sales_{q-i}$ = rolling sum of sales for preceding four quarters and $\sum_{i=0}^{3} Sales_{q-4-i}$ = rolling sum of sales for second preceding set of four quarters
9 TA	Total accruals to total assets (based on balance sheet accounts)	$\frac{\begin{bmatrix} (\Delta \text{Current Assets}_q\ [D40] - \Delta \text{Cash}_q\ [D36]) \\ -(\Delta \text{Current Liabilities}_q\ [D49] - \Delta \text{Current LTD}_q\ [D45]) \\ -\ \Delta \text{Deferred taxes}_q\ [D35] \\ -\ \text{Depreciation and amortization}_q\ [D5] \end{bmatrix}}{(\text{TA}_q + \text{TA}_{q-4})/2\ [D44]}$, where q = most recent quarter for which an earnings announcement was made a minimum two months prior to the end of quarter t, with $q \geq t\text{-}4$ $DX_q = X_q - X_{q-4}$ e.g., $\Delta \text{CurrentAssets}_{t-1} = \text{CurrentAssets}_{t-1} - \text{CurrentAssets}_{t-5}$
10 CAPEX	Capital expenditures to total assets (see example at end of this table)	$\frac{CAPEX_q}{(TA_q + TA_{q-4})/2\ [D44]}$, where q = most recent quarter for which an earnings announcement was made a minimum two months prior to the end of quarter t, with $q \geq t\text{-}4$ $CAPEX_q$ = rolling sum of four quarters (quarters $q\text{-}3$ through q) of Capital Expenditures *[D90]* (As D90 is fiscal-year-to-date, adjustments are made as needed to calculate the rolling sum of the preceding four quarters — see example at end of appendix.)
11. BP	Book to price	$\frac{\text{Book value of common equity}_q}{\text{Mktcap}_t}$, where q = most recent quarter for which an earnings announcement was made a minimum two months prior to the end of quarter t, with $q \geq t\text{-}4$ *Book value of common equity*$_q$ = book value of total common equity at the end of quarter q *[D59]* $Mktcap_t = P_t * Shares\ Outstanding_t$ = price at the end of the quarter t *[D14]*, multiplied by common shares outstanding at the end of quarter t [*D61*]
12 EP	Earnings to price	$\frac{\sum_{i=0}^{3} EPS_{q-i}}{P_t}$, where q = most recent quarter for which an earnings announcement was made a minimum two months prior to the end of quarter t, with $q \geq t\text{-}4$ EPS_q = earnings per share before extraordinary items for quarter q *[D19]* P_{it} = price at the end of the quarter t *[D14]* Thus, $\frac{\sum_{i=0}^{3} EPS_{q-i}}{P_t}$ = rolling sum of EPS for preceding four quarters, deflated by price

APPENDIX: Investment Signals (Continued)

Example of rolling sum of four quarters for cash flow variables (CAPEX [D90]):

We compute a trailing-twelve-month estimate of a firm's capital expenditure using a technique featured in Collins and Hribar (2000). To illustrate, consider the following fictitious time-series for ABC Company's capital expenditure (CAPEX). Assume ABC Company has a December year-end, and announces quarterly earnings 30 days after each quarter-end.

Year	Qtr	Item D90
1990	1	100
1990	2	300
1990	3	700
1990	4	1500
1991	1	150
1991	2	300
1991	3	850
1991	4	1200

If we form a portfolio at t = December 31, 1991, the most recent quarter for which an earnings announcement was made is q = September 30, 1991 (3^{rd} quarter of 1991). We require that the earnings announcement for quarter q is a minimum two months prior to the end of quarter t, and that q >= t-4. Thus, for the CAPEX calculation at q = September 30, 1991 (3^{rd} quarter of 1991). To compute CAPEX, we include the first three quarters of 1991's capital expenditures (850), plus the last quarter of 1990 (1500 - 700). Therefore, the rolling sum of four quarters for ABC as of the 3rd quarter of 1991 is CAPEX=850+800=1650.

Table 1: Description of Sample Firms

This table provides descriptive statistics on the firms included in our sample, averaged over the 56 quarters during the period 1985–1998. The sample consists of all firms with current individual stock recommendations in the Zacks database (defined as recommendations that have been outstanding for less than one year), provided the firm also has the required CRSP and Compustat information. Exchange listing is obtained at the time of the consensus recommendation.

PANEL A: Year

Year	Mean Obs per Quarter	Mean %age per Quarter	Mean Consensus per Quarter
1985	404.75	3.0%	3.21
1986	618.75	4.5%	3.45
1987	670.75	4.9%	3.61
1988	714.50	5.3%	3.65
1989	854.25	6.3%	3.56
1990	946.75	7.0%	3.60
1991	966.50	7.1%	3.58
1992	1,009.25	7.4%	3.68
1993	1,137.25	8.4%	3.70
1994	1,291.75	9.5%	3.84
1995	1,201.00	8.8%	3.82
1996	1,243.00	9.1%	3.79
1997	1,257.00	9.2%	3.92
1998	1,284.50	9.4%	3.97
Total sample	971.43		3.67

PANEL B: Exchange

Exchange	Mean Obs per Quarter	Mean %age per Quarter
NASD	569.66	56.3%
NYSE	263.96	28.6%
AMEX	131.64	14.3%
Other	6.16	0.7%
Total sample	971.43	100.0%

PANEL C: NYSE Size Decile

NYSE Mkt Cap Decile	Mean Capitalization ($000's)	NASD firms		NYSE/AMEX firms		Total sample	
		Mean Obs per Quarter	Mean %age per Quarter	Mean Obs per Quarter	Mean %age per Quarter	Mean Obs per Quarter	Mean %age per Quarter
10 (Largest)	8.99	13.79	1.3%	73.16	7.8%	86.95	9.0%
9	7.84	25.82	2.4%	64.38	6.9%	90.20	9.3%
8	7.19	35.98	3.4%	52.98	5.7%	88.96	9.1%
7	6.66	42.98	4.3%	45.04	4.9%	88.02	9.1%
6	6.19	48.34	4.8%	38.77	4.2%	87.11	8.9%
5	5.74	59.25	6.1%	34.02	3.7%	93.27	9.8%
4	5.31	64.14	6.5%	30.38	3.4%	94.52	9.9%
3	4.87	78.16	7.7%	28.16	3.2%	106.32	11.0%
2	4.37	87.95	8.7%	20.04	2.3%	107.98	10.9%
1 (Smallest)	3.60	113.25	11.3%	14.86	1.6%	128.11	12.8%
Total sample	6.08	569.66	56.3%	401.77	43.7%	971.43	100.0%

Table 2: Description of Analyst Recommendations

This table provides descriptive statistics on the analyst recommendations in our sample. Only firms with the required CRSP and Compustat information are included. We use all individual recommendations in the Zacks database that have been outstanding for less than one year. Each recommendation is reverse–scored from 5 (strong buy) to 1 (strong sell). We then compute a consensus recommendation, defined as the mean of all individual recommendations computed two days prior to the end of each calendar quarter. Firms are grouped into quintiles at the beginning of the next quarter based on either the *level* of, or the *change* in, the existing consensus recommendation. Panel A reports summary statistics on the recommendations in each of the *level* quintiles. Panel B reports summary statistics on the recommendations in each of the *change* quintiles, with all "no change" observations included in the middle quintile. Panel C reports the frequency distribution of observations each *change* quintile, conditional on its *level* quintile membership in the prior quarter.

PANEL A: Consensus Recommendation Level Quintiles (Strong BUY=5, HOLD=3, Strong SELL=1)

Quintile	Coded as	Mean Obs	Mean	Std Dev	Minimum	Maximum
Best=BUY	1.00	176.91	4.62	0.140	4.42	4.87
	0.75	194.77	4.07	0.171	3.77	4.38
	0.50	200.27	3.72	0.196	3.27	4.04
	0.25	186.32	3.37	0.179	2.95	3.75
Worst=SELL	0.00	213.16	2.76	0.238	1.81	3.13
Total sample (56 quarters)		971.43	3.67	0.198	3.09	3.99

PANEL B: Consensus Recommendation Change Quintiles (Change = Current – Prior)

Quintile	Coded as	Mean Obs	Mean	Std Dev	Minimum	Maximum
Best=Increase	1.00	192.07	0.52	0.121	0.37	1.06
	0.75	144.75	0.12	0.050	0.05	0.35
	0.50	294.24	0.00	0.003	–0.01	0.02
	0.25	144.80	–0.11	0.032	–0.23	–0.06
Worst=Decrease	0.00	198.60	–0.55	0.085	–0.88	–0.41
Total sample (55 quarters)		957.05	–0.01	0.033	–0.07	0.09

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

Prior Consensus Quintile	**Change in Consensus Quintiles** *Worst = Decrease*				**Best = Increase**	Total sample
Best = BUY	32.2%	14.8%	37.3%	9.8%	5.8%	18.3%
	25.5%	17.6%	25.2%	16.7%	15.1%	20.2%
	20.1%	19.3%	21.5%	18.2%	20.9%	20.7%
	16.7%	17.4%	19.6%	20.3%	26.0%	19.1%
Worst = SELL	9.3%	5.9%	46.4%	9.5%	29.0%	21.8%
Total sample	20.4%	14.9%	30.2%	14.9%	19.7%	100.0%

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 (RETF). Two different measures of analyst recommendations are used: the consensus recommendation level (CONS), and the change in the consensus measured over the prior quarter (CHGCONS). 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 consensus recommendation level (CONS), and Panel C reports future returns grouped by the change in the consensus recommendation (CHGCONS). ***, **, * indicates two–sided statistical significance at 1%, 5%, and 10%, respectively. Median results are based on Wilcoxon signed-rank tests, Mean results are based on t–statistics calculated with Hansen-Hodrick autocorrelation consistent standard errors.

PANEL A: Spearman Rank Correlations with Future Returns

Explanatory Variable	Continuous Expl. Variable		Categorical Expl. Variable	
	Mean	Median	Mean	Median
Consensus level (“CONS”)	+0.0312***	+0.0276 **	+0.0311***	+0.0350**
Consensus change (“CHGCONS”)	+0.0333***	+0.0384 ***	+0.0317***	+0.0286***

PANEL B: Market–Adjusted Returns by Consensus Recommendation Level Quintile

Quintile	Coded as	Mean	Median
Best = BUY	1.00	–0.003	–0.024
	0.75	–0.008	–0.024
	0.50	–0.015	–0.032
	0.25	–0.018	–0.033
Worst = SELL	0.00	–0.027	–0.055
BUY – SELL		+0.023 **	+0.034 ***

PANEL C: Market–Adjusted Returns by Consensus Recommendation Change Quintile

Quintile	Coded as	Mean	Median
Best = Increase	1.00	–0.004	–0.025
	0.75	–0.007	–0.015
	0.50	–0.022	–0.044
	0.25	–0.004	–0.023
Worst = Decrease	0.00	–0.031	–0.051
Increase – Decrease		+0.027 ***	+0.031 ***

Table 4: Quantitative Investment Signals and Future Returns

This table examines the Spearman rank correlation between future returns (RETF) and various quantitative investment signals. RETF is the market–adjusted return in the six months following the month of the recommendation. The twelve quantitative investment signals are describe in detail in the Appendix. 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 median for that quarter, and 0 otherwise. The net portfolio return is the mean difference in future returns between the portfolio of top firms (with binary variable equal to 1) and the portfolio of bottom firms (with the binary variable equal to 0). The %positive portfolio returns indicates the percentage of the 56 quarters in which the net portfolio return was above 0%. *** (**) [*] indicates statistical significance at 1% (5%) [10%] in two–tailed T-tests.

Explanatory Variable	Continuous Explanatory Variable	Binary Explanatory Variable				
		Definition	% Positive	Correlation	Mean net portfolio return	%Positive portfolio returns
RETP	+0.080 ***	*1 if greater than median 0 otherwise*	49.98%	+0.064 ***	+0.032 ***	76.79%
RET2P	+0.043 ***	*1 if greater than median 0 otherwise*	50.01%	+0.039 ***	+0.013 **	62.50%
TURN	–0.034 **	*1 if less than median 0 otherwise*	50.24%	+0.033 ***	+0.002	62.50%
SIZE	+0.088 ***	*1 if greater than median 0 otherwise*	50.02%	+0.077 ***	+0.016 *	64.29%
FREV	+0.099 ***	*1 if greater than median 0 otherwise*	49.99%	+0.091 ***	+0.042 ***	83.93%
LTG	–0.006	*1 if less than median 0 otherwise*	50.00%	+0.008	–0.000	53.57%
SUE	+0.053 ***	*1 if greater than median 0 otherwise*	50.00%	+0.040 ***	+0.018 ***	67.86%
SG	–0.025 *	*1 if less than median 0 otherwise*	49.99%	+0.025 **	+0.004	57.14%
TA	–0.081 ***	*1 if less than median 0 otherwise*	50.01%	+0.063 ***	+0.029 ***	85.71%
CAPEX	–0.021 **	*1 if less than median 0 otherwise*	50.01%	+0.023 ***	+0.015 ***	69.64%
BP	–0.016	*1 if greater than median 0 otherwise*	49.98%	+0.010	+0.000	50.00%
EP	+0.038 ***	*1 if greater than median 0 otherwise*	49.96%	+0.029 ***	+0.004	55.36%

Table 5: Summary Quantitative Variables and Future Returns

This table examines the correlation between the three summary quantitative variables and future returns. The dependent variable is future returns (RETF), defined as the market–adjusted return in the six months after portfolio formation. Three different summary variables are used: Momentum (the sum of four momentum signals: RETP, RET2P, FREV, SUE), Contrarian (the sum of the remaining eight investment signals), and QScore (the sum of all twelve binary investment signals). Each individual signal is described in detail in the Appendix. Panel A reports the Spearman rank correlation between each sum measure and future returns. We report results for both a continuous measure and a quintile measure of the sum variable (see Table 2). Panel B reports future returns grouped by QScore quintiles, Panel C reports future returns grouped by Momentum quintiles, and Panel D reports future returns for firms grouped by Contrarian quintiles. ***, **, * indicate two–sided statistical significance at 1%, 5%, and 10%, respectively, based on t–statistics calculated with Hansen-Hodrick autocorrelation consistent standard errors.

PANEL A: Spearman Rank Correlations with Future Returns

	Continuous Expl. Variable		Expl. Variable Quintile	
Explanatory Variable	Mean	Median	Mean	Median
QScore	+0.1253 ***	+0.1273 ***	+0.1236 ***	+0.1253 ***
Momentum	+0.0865 ***	+0.0908 ***	+0.0865 ***	+0.0908 ***
Contrarian	+0.0925 ***	+0.1016 ***	+0.0916 ***	+0.1010 ***

PANEL B: Market-adjusted Returns by *QScore* Quintile

FScore Sum	Coded as	Mean Obs per Qtr	Mean	Median
Best = 8, 9, 10, 11, 12	1.00	228.52	+0.0094	–0.0047
7	0.75	161.80	+0.0042	–0.0107
6	0.50	176.59	–0.0096	–0.0379
5	0.25	160.95	–0.0299	–0.0551
Worst = 0, 1, 2, 3, 4	0.00	226.09	–0.0477	–0.0803
Best – Worst			+0.0571 ***	+0.0770 ***

PANEL C: Market–Adjusted Returns by *Momentum* Quintile

Momentum Sum	Coded as	Mean Obs per Qtr	Mean	Median
Best = 4	1.00	161.84	+0.0141	–0.0047
3	0.75	217.88	–0.0012	–0.0219
2	0.50	195.77	–0.0165	–0.0308
1	0.25	217.89	–0.0305	–0.0548
Worst = 0	0.00	160.57	–0.0432	–0.0624
Best – Worst			+0.0573 ***	+0.0620 ***

PANEL D: Market–Adjusted Returns by *Contrarian* Quintile

Contrarian Sum	Coded as	Mean Obs per Qtr	Mean	Median
Best = 6, 7, 8	1.00	149.46	–0.0025	–0.0099
5	0.75	200.00	–0.0008	–0.0240
4	0.50	247.66	–0.0141	–0.0370
3	0.25	207.84	–0.0235	–0.0525
Worst = 0, 1, 2	0.00	148.98	–0.0390	–0.0802
Best – Worst			+0.0364 ***	+0.0786 ***

TABLE 6: Descriptive Statistics by Consensus Recommendation Quintile

This table examines the relation between the level of the consensus recommendation and twelve investment signals. The signals are described in detail in the Appendix. To construct this table, we sort all firms into quintiles in each of the 56 quarters by the level of their consensus stock recommendation. Table values represent the mean and median value of the investment signal for each recommendation quintile across the 56 quarters. Normative Direction indicates the sign of the variable's correlation with future returns from prior studies. Actual Direction indicates the sign of the variable's correlation with the analysts' consensus recommendation. Shaded rows represent variables for which the two directions are inconsistent. Correlation is the mean Spearman rank correlation between the consensus recommendation and a given investment signal across the 56 quarters. T–test is a test of the null that the mean value for the highest recommendation quintile equals the mean of the lowest quintile across the 56 quarters. *** indicates two–sided significance at 1%, based on t–statistics calculated with Hansen-Hodrick autocorrelation consistent standard errors.

Explanatory Variable		Normative Direction	Consensus Recommendation Quintile: BUY 1.00	0.75	0.50	0.25	SELL 0.00	Actual Direction	Correlation	T–test
Momentum Variables (Price or Earning)										
RETP	Mean	+	0.1508	0.1192	0.0827	0.0277	–0.0241	+	26.89%	6.95
	Median		0.1407	0.1033	0.0795	0.0254	–0.0278		***	***
RET2P	Mean	+	0.1758	0.1384	0.0946	0.0430	–0.0146	+	27.90%	7.63
	Median		0.1533	0.1223	0.0747	0.0392	–0.0178		***	***
FREV	Mean	+	–0.3274	–0.4703	–0.7619	–1.4352	–2.6510	+	34.59%	8.21
	Median		0.0000	–0.0175	–0.1618	–0.5450	–1.3660		***	***
SUE	Mean	+	1.0068	0.8898	0.5319	0.1230	–0.2711	+	32.10%	8.59
	Median		0.7246	0.6403	0.2946	0.0910	–0.1496		***	***
Contrarian Variables (Fundamental or Growth)										
EP	Mean	+	0.0580	0.0551	0.0543	0.0465	0.0262	+	11.89%	4.83
	Median		0.0567	0.0544	0.0563	0.0539	0.0498		***	***
BP	Mean	+	0.4727	0.4832	0.5281	0.5996	0.7499	–	–30.11%	–8.52
	Median		0.4211	0.4261	0.4676	0.5483	0.6784		***	***
SIZE	Mean	–	5.5629	6.1999	6.4940	6.2727	5.2186	+	4.29%	1.81
	Median		5.3657	5.9694	6.4410	6.3039	5.0130		***	***
TURN	Mean	–	52.2900	53.1011	52.5706	50.0011	41.1517	+	11.82%	3.82
	Median		53.2500	54.0000	53.2500	50.0000	36.7500		***	***
SG	Mean	–	1.2203	1.1875	1.1356	1.1032	1.0728	+	29.64%	7.41
	Median		1.1737	1.1432	1.1053	1.0799	1.0459		***	***
LTG	Mean	–	24.0312	20.1197	14.4616	9.7340	3.4313	+	27.24%	6.51
	Median		18.8900	15.5600	11.5975	7.7900	1.1500		***	***
TA	Mean	–	0.0213	0.0148	0.0052	0.0025	0.0018	+	10.62%	2.82
	Median		0.0091	0.0064	–0.0028	–0.0046	–0.0048		***	***
CAPEX	Mean	–	0.0887	0.0901	0.0897	0.0872	0.0766	+	4.24%	1.88
	Median		0.0658	0.0721	0.0701	0.0702	0.0604		***	***

TABLE 7: Regression of Recommendations on Explanatory Variables

This table reports the result when analyst recommendation metrics are regressed on various explanatory variables. Panel A (B) reports results when the dependent variable is the level of (changes in) the consensus recommendation. The explanatory variables are explained in detail in the Appendix. Shaded rows represent instances where the normative (NORM) and actual (ACTUAL) directions of correlation are inconsistent. The reported parameter estimates are the mean parameter estimates over 56 quarters for Panel A and 55 quarters for Panel B. ***, **, * indicates two–sided statistical significance at 1%, 5%, and 10%, respectively, based on t–statistics calculated with Hansen-Hodrick autocorrelation consistent standard errors.

PANEL A: Consensus Recommendation Levels ("CONS")

Mean R^2 25.70%
Mean F statistic 27.53

VARIABLE	NORM	ACTUAL	Mean $\hat{b}$	T
Intercept			+3.630	+22.842 ***
Momentum Variables (Price or Earning)				
RETP	+	+	+0.437	+10.964 ***
RET2P	+	+	+0.306	+8.559 ***
FREV	+	+	+0.031	+7.428 ***
SUE	+	+	+0.041	+4.890 ***
Contrarian Variables (Fundamental or Growth)				
EP	+	+	+0.683	+6.547 ***
BP	–	–	–0.321	–12.885 ***
TURN	–	+	+0.001	+8.383 ***
SIZE	+	–	–0.042	–1.876 *
LTG	–	+	+0.002	+5.355 ***
SG	–	+	+0.253	+4.140 ***
TA	–	+	+0.248	+3.632 ***
CAPEX	–	+	+0.136	+1.257

PANEL B: Consensus Recommendation Changes ("CHGCONS")

Mean R^2 14.88%
Mean F statistic 12.43

VARIABLE	NORM	ACTUAL	Mean $\hat{b}$	T	
Intercept			+0.171	+13.336	***
Prior consensus quintile			–0.431	–11.294	***
Momentum Variables (Price or Earning)					
RETP6	+	+	+0.262	+8.577	***
RET2P6	+	+	+0.004	+0.126	
FREV	+	+	+0.018	+13.654	***
SUE	+	+	+0.008	+5.531	***
Contrarian Variables (Fundamental or Growth)					
EP	+	–	–0.255	–3.033	***
BP	–	–	–0.024	–1.860	**
TURN	–	+	+0.000	+2.207	**
SIZE	+	–	–0.001	–0.120	
LTG	–	+	+0.000	+4.782	***
SG	–	+	+0.039	+5.591	***
TA	–	–	–0.029	–2.186	**
CAPEX	–	+	+0.021	+1.178	

TABLE 8: Future Returns, Analyst Recommendations, and Investment Signals

This table reports regressions of future returns on analyst recommendations and on various investment signals. Future returns are defined as the market–adjusted return in the six months after the month of the recommendation (RETF). Analyst recommendations used are: the quintile of the consensus recommendation level (QCON), and the quintile of the change in the consensus measured over the prior quarter (QCHGCON). QFITCON and QFITCHGCON are fitted values of QCON and QCHGCON from Panels A and B of Table 7, respectively. The reported parameter estimates are the mean parameter estimates from the quarterly regressions. ***, **, * indicates two−sided statistical significance at 1%, 5%, and 10%, respectively, based on t−statistics calculated with Hansen-Hodrick autocorrelation consistent standard errors.

PANEL A: Consensus Recommendation Levels Quintiles (QCON)

	Model A1 *Analysts Alone*		**Model A2** *Analysts & QScore*		**Model A3** *Analysts & Binary Signals*		**Model A4** *Analysts & Fitted Value*	
Parameter	**Estimate**	**T-stat**	**Estimate**	**T-stat**	**Estimate**	**T-stat**	**Estimate**	**T-stat**
Intercept	-0.0257	-2.13 **	-0.0484	-2.79 ***	-0.0673	-2.65 **	-0.0336	-2.58 **
QCON	0.0226	1.83 *	0.0108	1.22	0.0076	1.31	0.0074	1.42
QScore			0.0562	3.23 ***				
QFITCON							0.0300	3.26 ***
RETP					0.0175	3.31 ***		
RET2P					0.0019	0.32		
FREV					0.0324	17.99 ***		
SUE					0.0017	0.31		
EP					0.0021	0.57		
BP					-0.0089	-1.41		
TURN					0.0011	0.17		
SIZE					0.0078	0.66		
LTG					0.0007	0.11		
SG					0.0007	0.44		
TA					0.0268	9.46 ***		
CAPEX					0.0134	2.58 **		

PANEL B: Consensus Recommendation Changes Quintiles (QCHGCON)

	Model B1 *Analysts Alone*		**Model B2** *Analysts & QScore*		**Model B3** *Analysts & Binary Signals*		**Model B4** *Analysts & Fitted Value*	
Parameter	**Estimate**	**T-stat**	**Estimate**	**T-stat**	**Estimate**	**T-stat**	**Estimate**	**T-stat**
Intercept	-0.0262	-1.85 *	-0.0522	-2.86 ***	-0.0690	-2.64 **	-.0316	-1.96 *
QCHGCON	0.0225	5.26 ***	0.0190	3.80 ***	0.0159	15.73 ***	0.0173	4.07 ***
QScore			0.0551	3.34 ***				
QFITCHGCON							0.0159	2.75 ***
RETP					0.0176	3.51 ***		
RET2P					0.0014	0.31		
FREV					0.0319	15.00 ***		
SUE					0.0027	0.52		
EP					0.0011	0.61		
BP					-0.0080	-1.27		
TURN					0.0000	0.00		
SIZE					0.0065	0.56		
LTG					-0.0004	-0.06		
SG					0.0002	0.10		
TA					0.0261	10.18 ***		
CAPEX					0.0132	2.43 **		

TABLE 9: Future Returns by Quantitative Scores and Analyst Recommendations

This table reports the market-adjusted return in the six months following the recommendation. Firms are grouped by their quantitative measures (QScores) and consensus recommendations. Panels A, B, and C report results for the recommendation level quintiles (QCON), change quintiles (QCHGCON), and a combined strategy of level and change quintiles, respectively. ***, **, * indicate two-sided statistical significance at 1%, 5%, and 10%, respectively.

PANEL A: Market–Adjusted Returns by Recommendation *Level* Quintile and *QScore* Quintile

		Consensus Recommendation Level Quintile											
		Worst=SELL: 0.00		0.25		0.50		0.75		1.00: Best=BUY			
QScore Quintile		Obs	Mean	Obs	Mean	Obs	Mean	Obs	Mean	Obs	Mean	BUY - SELL	*t p*
Worst=LOW	0.00	72.51	–0.0445	48.07	–0.0350	41.24	–0.0355	34.76	–0.0510	32.87	–0.0652	–0.0207	–1.37
	0.25	42.51	–0.0318	31.33	–0.0250	29.93	–0.0269	30.55	–0.0275	29.09	–0.0358	–0.0040	–0.22
	0.50	37.47	–0.0080	32.82	–0.0155	35.09	–0.0074	36.69	–0.0158	36.91	+0.0020	+0.0100	+0.58
	0.75	26.67	–0.0049	28.49	–0.0131	35.96	–0.0080	38.29	+0.0101	34.85	+0.0226	+0.0276	+1.83**
Best=HIGH	1.00	30.27	–0.0066	44.04	+0.0020	58.42	–0.0002	55.13	+0.0196	44.15	+0.0258	+0.0324	+3.30***
HIGH–LOW			+0.0379		+0.0370		+0.0353		+0.0706		+0.0910		
t			+2.23		+2.73		+2.72		+4.77		+7.87		
p			***		***		***		***		***		
Overall analysts' level recommendations = Buy−Sell (*see also Table 3 Panel B*)												+0.0216	+1.66*
Overall quantitative strategy = High−Low (*see also Table 5 Panel B*)												+0.0541	+4.47***
DISAGREE = Low&Buy–High&Sell												–0.0586	–4.03***
AGREE = High&Buy–Low&Sell												+0.0703	+3.78***

PANEL B: Market–Adjusted Returns by Recommendation *Change* Quintile and *QScore* Quintile

		Consensus Recommendation Change Quintile											
		Worst=DECR: 0.00		0.25		0.50		0.75		1.00: Best=INCR			
QScore Quintile		Obs	Mean	Obs	Mean	Obs	Mean	Obs	Mean	Obs	Mean	Incr- Decr	*t p*
Worst=LOW	0.00	59.42	–0.0623	29.65	–0.0270	72.49	–0.0553	25.02	–0.0368	39.84	–0.0326	+0.0297	+2.92***
	0.25	35.60	–0.0502	21.91	–0.0088	50.76	–0.0346	21.44	–0.0228	31.64	–0.0141	+0.0361	+4.55***
	0.50	33.82	–0.0229	25.44	–0.0043	55.36	–0.0138	26.36	–0.0053	35.93	+0.0022	+0.0251	+2.25**
	0.75	28.33	–0.0035	25.65	–0.0033	47.55	+0.0041	26.38	+0.0040	34.60	+0.0112	+0.0148	+1.17
Best=HIGH	1.00	35.33	+0.0026	40.51	+0.0206	62.78	+0.0037	43.67	+0.0067	47.36	+0.0162	+0.0136	+1.83**
HIGH–LOW			+0.0649		+0.0475		+0.0590		+0.0435		+0.0488		
t			+4.06		+2.55		+5.73		+2.86		+3.48		
p			***		***		***		***		***		
Overall Analysts' change recommendations = Incr−Decr (*see also Table 3 Panel C*)												+0.0268	+6.07***
Overall Quantitative strategy = High−Low (*see also Table 5 Panel B*)												+0.0541	+4.47***
DISAGREE = Low&Incr–High&Decr												–0.0352	–2.33***
AGREE = High&Incr–Low&Decr												+0.0785	+5.29***

Table 9: Future Returns by Quantitative Scores and Consensus Recommendation Levels (Continued)

PANEL C: Market–Adjusted Returns by Combination of Recommendation *Level and Change* Quintiles and *QScore* Quintile

		Consensus Recommendation Combinations of Levels and Changes								
		Worst = SELL and DECR		Other		Best = BUY and INCR		BUY&INCR - SELL&DECR		
Qscore Quintile		Obs	Mean	Obs	Mean	Obs	Mean		*t*	*p*
Worst=LOW	**0.00**	24.33	-0.0689	196.44	-0.0438	9.02	-0.0476	0.0183	0.95	
	0.25	12.87	-0.0694	142.60	-0.0274	8.23	0.0118	0.0847	3.23	***
	0.50	10.65	-0.0087	158.11	-0.0127	10.22	0.0180	0.0268	1.14	
	0.75	6.71	0.0144	147.98	0.0024	9.58	0.0231	0.0088	0.31	
Best=HIGH	**1.00**	7.07	-0.0319	211.78	0.0086	13.27	0.0246	0.0558	4.02	***
HIGH–LOW			0.0374		0.0524		0.0666			
t			2.15		5.57		3.10			
p			**		***		***			
Overall analysts' combined recommendations = Buy&Incr−Sell&Decr								+0.0529	+4.32	***
Overall quantitative strategy = High−Low (*see also Table 5 Panel B*)								+0.0541	+5.55	***
DISAGREE = Low&(Buy&Incr)–High&(Sell&Decr)								-0.0190	-0.81	
AGREE = High&(Buy&Incr)–Low&(Sell&Decr)								0.0935	+4.97	***

TABLE 10: Cumulative Excess Returns Over Various Holding Periods

This table reports the market-adjusted returns over various holding periods following the recommendation. Firms are grouped by their quantitative measure (QScore, Momentum, Contrarian) and consensus recommendations. Panel A reports the mean difference in market-adjusted returns between the extreme consensus recommendation level quintiles (BUY-SELL) within each of the quantitative measure quintiles. Panels B repeats the analyses for changes in recommendations. ***, **, * indicate two-sided statistical significance at 1%, 5%, and 10%, respectively, based on t–statistics calculated with Hansen-Hodrick autocorrelation consistent standard errors.

PANEL A: Mean market–adjusted return difference between extreme recommendation *level* quintiles (BUY-SELL) within each *quantitative* quintile

Holding Period	Within Quantitative Quintile Worst=LOW: 0.00	0.25	0.50	0.75	Best=HIGH: 1.00
Within QScore Quintile					
1 month	-0.0024	-0.0091	0.0045	0.0062	0.0071**
3 months	-0.0051	-0.0014	0.0115	0.0223***	0.0192***
6 months	-0.0207	-0.0040	0.0100	0.0276**	0.0324***
9 months	-0.0451**	-0.0363*	0.0080	0.0415**	0.0448***
12 months	-0.0732***	-0.0390	-0.0038	0.0379	0.0502***
Within Momentum Quintile					
1 month	0.0002	-0.0068	0.0006	0.0033	0.0054
3 months	0.0009	-0.0077	0.0031	0.0071	0.0262***
6 months	-0.0060	-0.0251**	0.0013	0.0083	0.0279***
9 months	-0.0198	-0.0468***	0.0074	-0.0005	0.0380***
12 months	-0.0495	-0.0663***	0.0004	0.0035	0.0363*
Within Contrarian Quintile					
1 month	0.0005	0.0047	0.0045	0.0111***	0.0057
3 months	0.0150	0.0169***	0.0183***	0.0284***	0.0235***
6 months	0.0041	0.0303***	0.0255***	0.0348***	0.0474***
9 months	-0.0206	0.0226	0.0307**	0.0393**	0.0610***
12 months	-0.0446	0.0159	0.0259	0.0349	0.0695***

PANEL B: Mean market–adjusted return difference between extreme recommendation *change* quintiles (BUY-SELL) within each *quantitative* quintile

Holding Period	Within Quantitative Quintile Worst=LOW: 0.00	0.25	0.50	0.75	Best=HIGH: 1.00
Within QScore Quintile					
1 month	0.0108***	0.0087***	0.0095***	0.0065**	0.0062**
3 months	0.0166***	0.0213***	0.0156***	0.0088	0.0114***
6 months	0.0297***	0.0361***	0.0251***	0.0148	0.0136**
9 months	0.0280***	0.0528***	0.0309***	0.0253*	0.0186***
12 months	0.0208	0.0511***	0.0323**	0.0356***	0.0245***
Within Momentum Quintile					
1 month	0.0016	0.0129***	0.0122***	0.0090***	0.0038
3 months	0.0114*	0.0156***	0.0144***	0.0164***	0.0119*
6 months	0.0257***	0.0251***	0.0337***	0.0214***	0.0166
9 months	0.0264***	0.0368***	0.0459***	0.0223***	0.0325***
12 months	0.0124	0.0276	0.0448***	0.0346***	0.0463***
Within Contrarian Quintile					
1 month	0.0183***	0.0043	0.0072***	0.0092***	0.0106***
3 months	0.0309***	0.0132**	0.0165***	0.0067	0.0165***
6 months	0.0450***	0.0313**	0.0170***	0.0137	0.0288***
9 months	0.0522***	0.0292***	0.0330***	0.0297***	0.0260***
12 months	0.0624***	0.0269**	0.0240**	0.0336***	0.0322***

FIGURE 1: Data accumulation periods relative to portfolio formation date

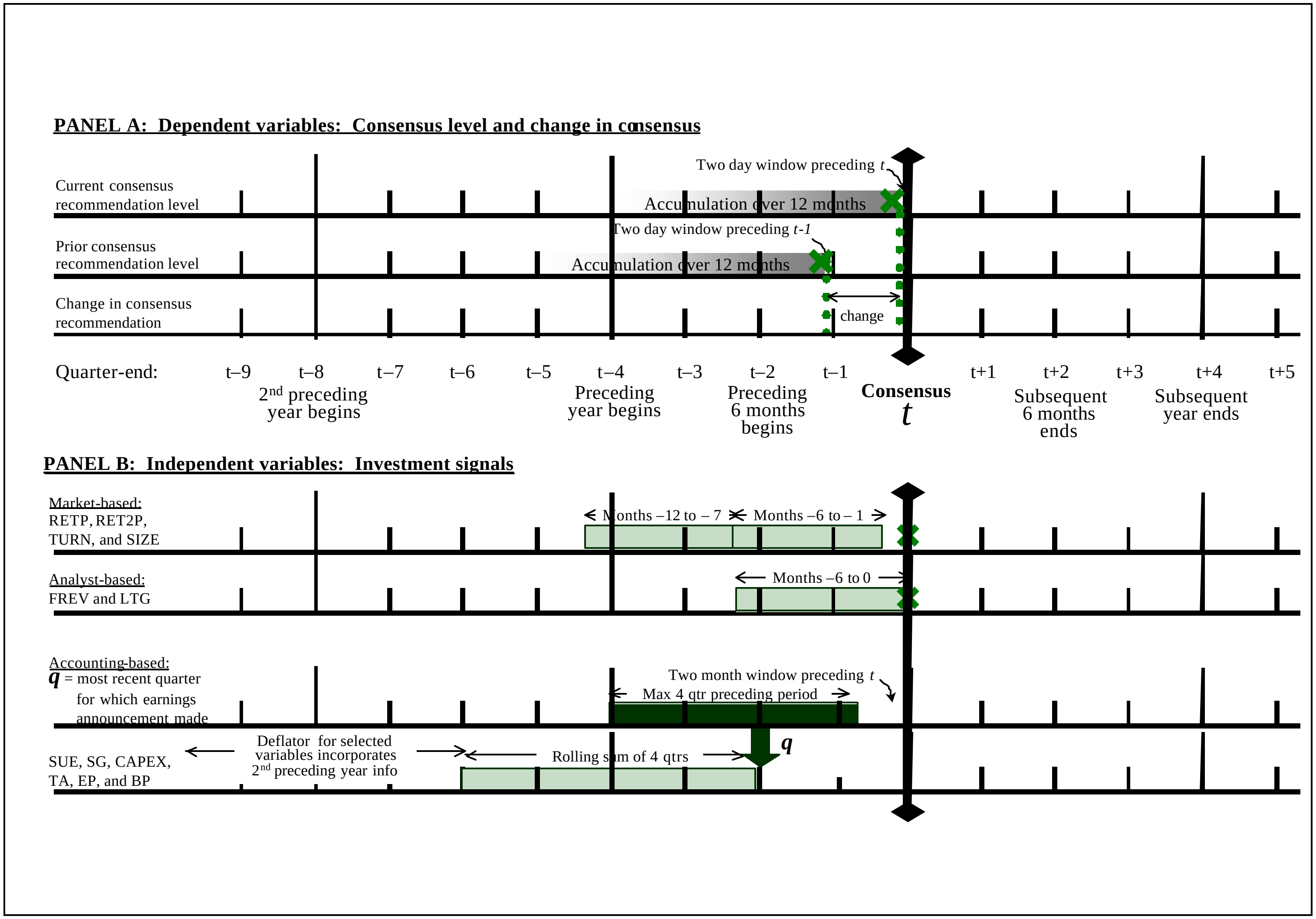
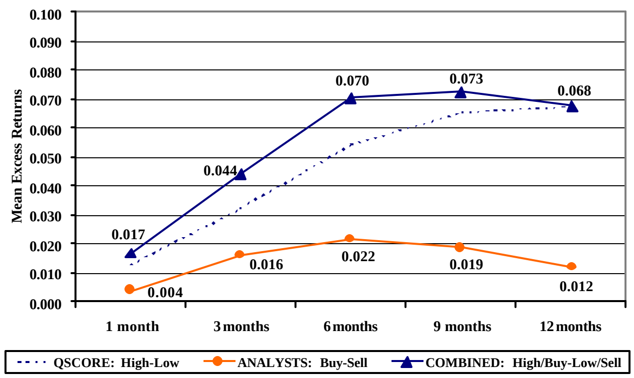
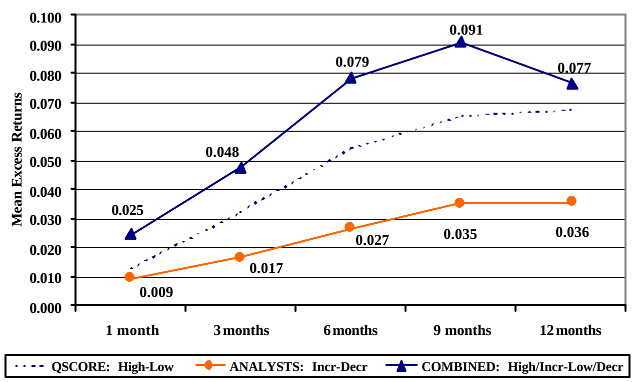


FIGURE 2. Cumulative Excess Returns to Analyst Recommendation Strategies (Level and Change) in Combination with Quantitative Quintiles

PANEL A: Consensus Recommendation Levels Quintiles (QCON), Separately and in Combination with Quantitative Quintiles (QScore)



PANEL B: Consensus Recommendation Changes Quintiles (QCHGCON), Separately and in Combination with Quantitative Quintiles (QScore)



PANEL C: Consensus Recommendation Levels Quintiles (QCON) and Changes Quintiles (QCHGCON), Separately and in Combination with Quantitative Quintiles (QScore)

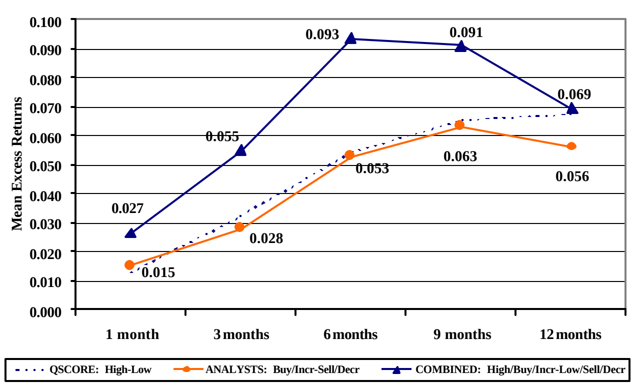
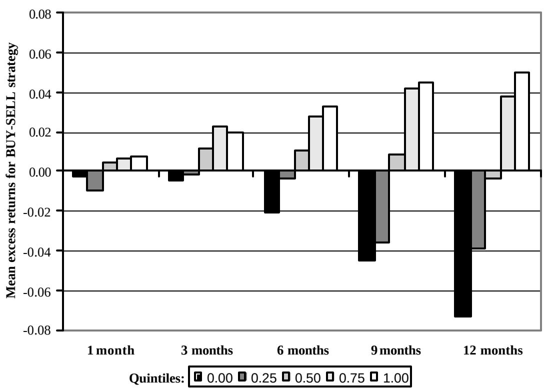


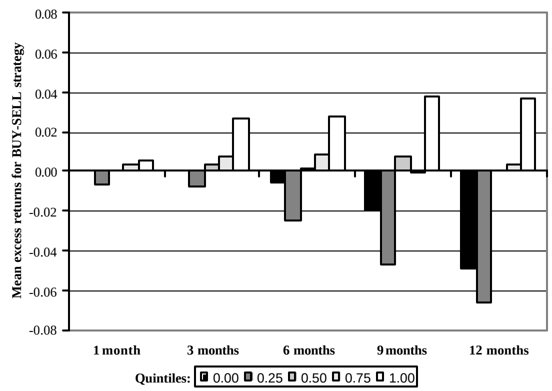
FIGURE 3. Cumulative Excess Returns to Analyst Recommendation Strategies Across Quantitative Quintiles

PANEL A: Hedge Returns to Extreme Recommendation *Level* Quintiles (QCON) Across Quantitative Quintiles

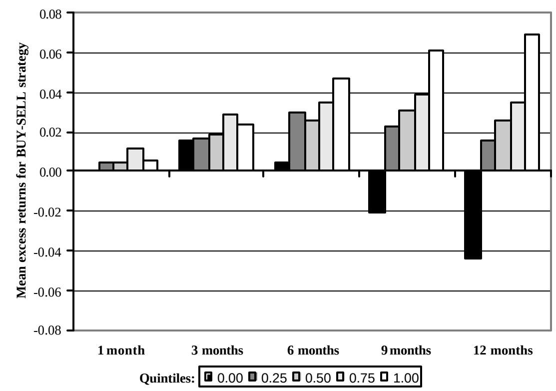
Qscore



QMomentum

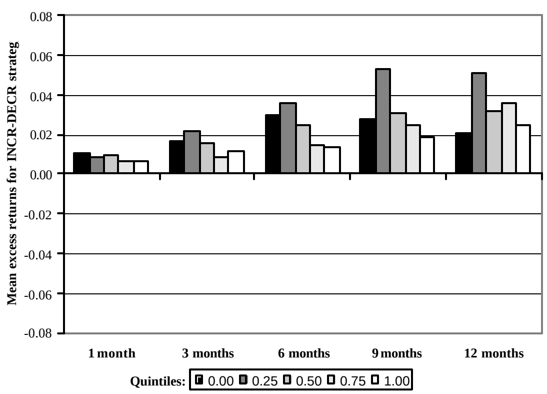


QContrarian

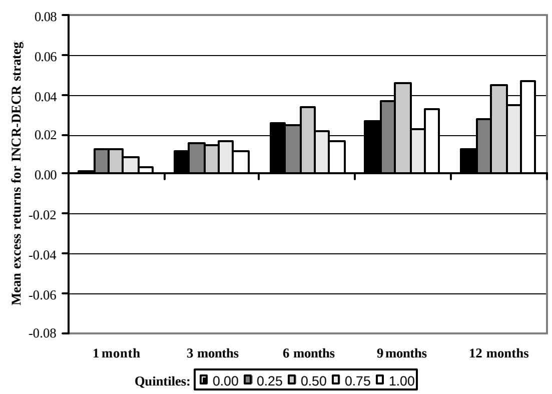


PANEL B: Hedg e Returns toExtreme Recommendation *Change* Quintiles (QCHGCON) Across Quantitative Quintiles

Qscore



QMomentum



QContrarian