Analyzing the analysts: When do recommendations add value?

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Abstract

We show that, consistent with economic incentives, 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 favorable quantitative characteristics (i.e., high value and positive momentum). Among stocks with unfavorable 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]

The focus of this study is on analyst stock recommendations. 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, their stock 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.

Our study investigates the source of the investment value provided by analyst stock recommendations and changes in recommendations. One possible source of the value is the ability of analysts to collect and process information about firms that allows them to identify undervalued or overvalued stocks. Alternatively, it is possible that recommendations derive their value by tilting towards stocks with certain stock characteristics that predict future returns. We assess the contribution of these sources of potential value.

We also assess the extent to which sell-side analysts make full use of available information signals in formulating stock recommendations, and whether their recommendations are affected by economic incentives in their operating environment. We find that analysts do not fully take into account the ability of various stock characteristics to predict returns. Moreover, our evidence shows that the direction of the

[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).

bias in analyst stock recommendations is in line with economic incentives faced by sell-side brokerage firms.

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. 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. We profile analyst preferences in terms of 12 measures that have a demonstrated ability to forecast cross-sectional returns in prior studies. 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.

Our results provide a context for understanding the findings from several prior studies. First, we show that stocks favorably recommended by the analysts, on average, outperform stocks unfavorably recommend by them. 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 other signals, the marginal predictive ability of the *level* of analyst recommendation is not significant.

Second, we show that a key reason for the poor performance of the *level* variable is analysts' failure to quickly downgrade stocks rejected by the other investment signals. For stocks where the other signals predict low future returns, we find that favorably recommended stocks actually significantly *underperform* unfavorably recommended

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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.

stocks. For this subset of stocks, favorable analyst recommendations may temporarily support prices and delay the eventual incorporation of information 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.

Third, we find that *upgraded* stocks outperform *downgraded* stocks. Our tests show that the predictive power of *changes* (revisions) in analyst recommendation is more robust than the predictive power of the *level* of their recommendations. Specifically, we find that recommendation changes add value to characteristic-based investment strategies that include 12 other predictive variables. Further analysis shows that the superior performance of recommendation *changes* is due largely to the fact that recommendation *changes* are less affected by the growth bias that afflicts the *level* variable.

Fourth, our results contribute to the literature on analyst objectivity. Prior studies comparing the earning forecasts and stock recommendations of analysts from affiliated and unaffiliated firms (e.g., Lin and McNichols (1998) and Michaely and Womack (1999)) show that existing, and potential, investment banking relationships can affect analyst judgment. Our results indicate that the economic consequences of sell-side incentives that impair analyst objectivity can also extend to the type of the stocks they choose to recommend. Specifically, our findings suggest that analyst recommendations may be partly driven by incentives that are not entirely related to the investment performance of their recommendations.

Most sell-side analysts work for brokerage houses whose primary businesses are investment banking and sales and trading – the research department itself typically generates no significant revenue. Growth firms, and firms with higher trading activity, make for more attractive investment banking clients. These firms also tend to be widely held by the institutional clients that place trades with the brokerage houses. Thus, sell-side analysts have significant economic incentives to publicly endorse high growth stocks with glamour characteristics. These incentives may cause analysts to, knowingly or otherwise, tilt their attention and recommendations in favor of growth stocks.

However, our results 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. For most contrarian signals, the correlation with analysts' stock recommendations is, in fact, directionally opposite to the variable's correlation with future returns. Whether this style bias is deliberate or not, our results show that it does adversely affect the investment value of analyst stock recommendations.

Partly due to this bias, the *level* of analyst recommendation provides little incremental investment value over the other investment signals. However, recent *changes* in recommendations do 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.

Finally, this paper provides a link between the literature on analyst recommendations and studies on the predictability of cross-sectional returns. Earlier studies by 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.[4] Barber et al. (2001a) extends 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' preferences for stock characteristics that predict future returns. 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 and we find important difference between the value of recommendation levels and changes.

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

[4] Specifically, Womack (1996) examines 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.

recommendations. Section 6 summarizes our findings and discusses some of their implications.

2. Analyst recommendations and stock characteristics

The first part of this study provides a *descriptive* profile of firms that receive stronger recommendations, as well as firms that analysts tend to upgrade or downgrade. Recent studies by Finger and Landsman (1999) and Stickel (1999) also examine analyst preferences for various stock characteristics, but there are important differences. Given our interest in the role of analyst recommendations in investment decisions, the stock characteristics that we choose to examine have a demonstrated ability to predict returns in the literature. In addition to providing a descriptive profile, we are also interested in assessing how analysts' tilt towards various characteristics help or hurt the performance of their recommendations. Moreover, we examine the stock characteristics that are associated with both *levels* of and *changes* in analyst recommendations while these two earlier studies focus only on the *level* of the recommendations.

2.1 Predictive Variables

We consider twelve variables that have demonstrated their ability to predict cross-sectional returns. These variables are summarized below. Appendix A presents more detailed information on how each variable is computed.

<u>2.1.1 Momentum and Trading Volume</u> – 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 last month of the recommendation quarter.

Prior studies also show that recent earnings momentum predicts cross-sectional returns (e.g., Bernard and Thomas (1989), and Chan, Jegadeesh, Lakonishok (1996)). 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 over the six months prior to the last month of the recommendation quarter, scaled by price. **SUE** is the unexpected earnings for the most recent reporting quarter, scaled by its time-series standard deviation over the eight preceding quarters.[5]

TURN is a measure of the average daily volume turnover for the stock in the six months preceding the last month of the recommendation quarter. Lee and Swaminathan (2000) show that high (low) volume stocks exhibit glamour (value) characteristics, and earn lower (higher) returns in subsequent months.[6] They argue that TURN is a contrarian signal, and that high (low) turnover stocks are over-valued (under-valued) by investors.

If analysts base their recommendations on evidence of price and earnings momentum, then we would expect past winners and high earnings momentum stocks to receive the most favorable recommendations. Similarly, if analysts rely on the predictive power of trading volume, we would expect their recommendations to tilt more favorably towards lower-volume stocks than higher-volume stocks.

<u>2.1.2 Valuation Multiples</u> – 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.[7] In either case, if analysts pay attention to the predictive ability of these multiples, we would expect high EP (and high BP) firms to receive more favorable recommendations.

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[5] The "most recent reporting quarter" is defined as the immediate prior quarter for which an earnings announcement was made, provided the announcement date occurs at least two months before the end of the recommendation quarter.

[6] 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.

[7] See, for example, the discussions in Fama and French (1992) and Lakonishok et al. (1994) for two alternative interpretations of the evidence.

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.[8] 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 results, low SGI (and low LTG) firms should receive more favorable recommendations.

2.1.4 Firm Size – Banz (1981) and Reinganum (1981), 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 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

[8] 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.

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, although high accruals may be symptoms of managerial manipulation in some instances, they 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 subsequent 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 in formulating their stock picks, 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, this set contains most, if not all, of the important variables that are known to predict returns. Analysts may be explicitly or intuitively aware of the ability of these variables to predict future returns. 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.[9] 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

[9] 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.

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 of the investment signals are available for that quarter.

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 q as the most recent quarter for which an earnings announcement was made at least two months prior to the end of quarter t. We then calculate the accounting ratios that we describe in Appendix A using data from financial statements for quarters q through $q-4$. We compute holding period returns starting with the first trading day of quarter $t+1$.

These procedures ensure that: (1) the latest financial statements are available to the market at the start of our holding period, (2) this financial information is reasonably fresh for all sample firms, and (3) the holding period returns we report can be earned by implementable trading strategies.

3.2 Data Description

Our data collection procedure yields 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 increases over time from 1985 through 1998. Panel B shows that approximately 56% (44%) of our observations are Nasdaq (NYSE/AMEX) firms. Finally, Panel C shows that these observations are about evenly distributed across the NYSE size deciles, but the size distribution varies by exchange. In additional analyses not reported here, we find that the firms in the sample span a large number of different industries, and no single industry (classified by two-digit SIC) represents 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).[10] 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). In our sample, analysts were slightly more likely to downgrade a firm than upgrade it (mean change over 55 quarterly observations = –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

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[10] 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).

[11] Additional analyses (not reported) show that less than 5% of the individual recommendations are "sells" or "strong sells", close to one-third of the recommendations are "holds" and just less than two-third are "buys" or "strong buys."

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 recommendation. Conversely, 29.0% of the firms in the bottom quintile of prior consensus recommendations appear in the top *changes* quintile.

4. Empirical Results

4.1 Analyst Recommendations and Future Returns

Table 3 provides evidence on the predictive ability of analyst stock recommendations. This table reports market-adjusted returns for a six-month holding period.[12] Panel A reports the Spearman rank correlation between the two recommendation measures and market-adjusted returns for the six months following the end of each quarter. 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 autocorrelation adjusted statistics (see Appendix B for details on the computation of autocorrelation adjusted *t*-statistics); the Median results are based on two-sided Wilcoxon signed-rank tests. This table reports the correlations for both the continuous variables, as well as the categorical variables, based on the quintile assignments.

Table 3 (Panel A) confirms the results in prior studies that both CONS and CHGCONS are correlated with future returns. 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). The market-adjusted returns are mostly negative because we use the value-weighted index as the benchmark and the large capitalization stocks that have large weights in the index had relatively high returns during our sample period.

The results in Table 3 (Panel B) indicate that a strategy that buys the quintile of stocks with the highest recommendation and sells the quintile of stocks with the lowest recommendation earns 2.3% over the next six months. In contrast, Barber et al. (2001a)

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[12] We define market-adjusted return as raw returns minus contemporaneous value-weighed index returns (see Appendix A).

report that a similar strategy, rebalanced daily, earns 14.5% per year. The main reason for the difference in results is that we hold the positions for six months while Barber et al. (2001a) revise them daily. Therefore, the implicit strategy in Barber et al. is much more transaction intensive. Also, our results provide a measure of the level of mispricing that consensus recommendations are able to detect. This result cannot be inferred from the profits to the Barber et al. strategy because the composition of their portfolios changes daily. Our results indicate that the consensus recommendation level is associated with a relative mispricing of 2.3% for the most favorably recommended stocks relative to the least favorably recommended stocks over the next six months.[13] Viewed from this perspective, the economic significance of the amount of mispricing that analysts are able to detect appears fairly small.

The results in Table 3 (Panel C) indicate that a trading strategy that buys stocks in the top CHGCONS group and sells stocks in the bottom CHGCONS group earns 2.7% over the next six months. The relation between CHGCONS and future returns, however, is not monotonic as the no changes category (0.50) earns lower returns than the adjacent categories. Most of the profits to the strategy based on CHGCONS are due to lower returns for the downgrades.

The returns earned by the extreme changes categories are smaller in magnitude than the returns for recommendation changes in Womack (1996). The difference is mainly due to the fact that Womack considers changes to the extreme recommendation levels (to strong buys or to strong sells), while we consider the performance of the top and bottom CHGCONS quintiles. Therefore, there are many more stocks in our extreme quintiles than in the sample of changes considered by Womack. Also, Womack considers the performance of recommendation changes starting from the event date while we consider the performance staring from a pre-determined calendar date. As Barber et al. points out, Womack's event time analysis does not yield an implementable investment strategy. As in Barber et al., we consider a calendar time trading strategy, which can be implemented in practice.

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[13] As reported in more detail later, we do not observe a significant drift after 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 directions reported in prior studies. The two exceptions are SIZE and BP. In the 1985-1998 period, large firms outperformed small firms 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 positive relation between BP and future returns. But in our sample period, value firms did not outperform growth firms. In fact, we find a negative (but statistically insignificant) correlation between BP and future returns. We also find a statistically insignificant negative correlation between LTG and future returns, while La Porta (1996) reports a significantly negative correlation.

In general, firms with positive price momentum (RETP and RET2P), positive earning momentum (FREV and SUE), and low trading volume (TURN) earn higher returns over the next six months. Similarly, low SG firms, low TA and CAPEX firms, as well as high EP firms, earn 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 expected to be 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 rely on the evidence in the prior literature to determine the expected sign of the correlation between the variables and future returns, rather than on the evidence during our sample period.[14] We then compute the **Qscore** for each stock by aggregating its 12 binary signals. This aggregation process gives us a summary measure that captures how these signals work together in quantitative

[14] For example, we expect a negative correlation between SIZE and future returns based on the evidence in Banz (1981) and Reinganum (1981), but we find a positive correlation in our sample. Based on prior evidence, we assign a binary score of 1 if SIZE is less than the median and 0 otherwise.

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 **Momentum** score by aggregating the binary scores across the momentum signals RETP, RET2P, FREV, and SUE. We aggregate the binary scores across the remaining signals (excluding SIZE) 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 are also 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 reports the proportion of sample quarters (out of a total of 56) in which the net portfolio return would have been above 0%. This column shows that the top three predictive variables (**RETP**, **FREV**, and **TA**) produce positive net portfolio returns in at least 75% of the sample quarters.

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 signals, excluding firm size), and **QScore** (the sum of all twelve binary signals). Panel A reports the Spearman rank correlation between each summary measure and future returns. We pool together some of the extreme Qscore and Contrarian score categories so that the extreme portfolios have at least about 100 stocks per quarter on average. Panels B, C and D present the market-adjusted six-month returns for equal-weighted portfolios of stocks with different levels of Qscores, Momentum scores and Contrarian scores, respectively.

Panel B shows that the mean (median) difference between top and bottom QScore category returns is 6.99% (6.85%). The mean (median) difference for the extreme categories ranked by Momentum score (Panel C) is 5.73% (6.20%). The mean (median) return difference between the extreme Contrarian categories (Panel D) is 3.10% (2.74%). For all three variables, the decline in the mean and median returns is approximately monotonic as we move down the category rankings. 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 that most of the investment signals we consider reliably predict returns in our sample period. 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 of each of the 12 investment signals by recommendation quintiles. Panel A reports the results grouped by recommendation *levels*; Panel B reports results grouped by recommendation *changes*. 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 consensus recommendation in our sample. We also report the Spearman rank correlation between each variable and the consensus recommendation. When this rank correlation is 10% or higher, the direction of the relation is unambiguous, and table values are generally monotone across recommendation quintiles. These variables are indicated by a "+" or "-" symbol under the heading "Actual Directions." When the rank correlation is below 10%, the directional relation is less clear, as indicated by the symbol "?" under the heading "Actual Direction."

Panel A indicates that the *level* of analysts' consensus recommendations exhibit a strong preference for positive momentum stocks – the Spearman rank correlation between analyst recommendations and the four momentum variables range from 26.9% to 34.6%. In particular, analysts seem to most favorably recommend past winners, and firms with recent upward earnings forecast revisions (FREV) and positive earnings surprises (SUE).

Perhaps the most striking result in Panel A is the consistency with which the consensus recommendation contradicts the expected normative usage of the Contrarian variables. In six out of seven 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 low BP, high SG, high LTG, high TA, and high CAPEX stocks. Except for CAPEX, each of these correlations is above 10%. 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.[15]

Panel B reports results for groups formed using quarterly *changes* in the consensus recommendation. Focusing on the Momentum variables, we find that the stocks analysts upgrade tend to exhibit positive price (RETP) and earnings (SUE and FREV) momentum. However, the correlation levels are generally lower than those in Panel A, and only the correlation with RETP is higher than 10%.

More importantly, the Panel B results for the Contrarian signals stand in sharp contrast to those observed in Panel A. First, this panel shows that, in virtually all cases, the *change* in the consensus recommendation is correlated with the signal in the "right" direction. For example, recommendation *changes* are negatively correlated with TURN, SG, LTG, TA, and CAPEX, but positively correlated with BP. Second, the results show that the degree of correlations tends to be modest (all are below 10%).

Table 7 provides additional evidence in a multivariate setting. This table presents the estimates of the regression coefficients when analyst recommendation is regressed on the 12 explanatory variables. For ease of comparison of coefficients across signals, we standardize each signal. We divide the difference between the signals and the corresponding cross-sectional means by the respective cross-sectional standard deviations. We then follow the Fama-MacBeth procedure and fit the regressions separately for each quarter, and report the time-series averages of the slope coefficients. Because analyst recommendations tend to be stable across quarters, the regression

[15] 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%).

coefficients are serially correlated. Therefore, we use autocorrelation-consistent standard errors of the time-series averages of the slope coefficients to compute the *t*-statistics, based on procedures that we describe in Appendix B.

Panels A and B report the results when the dependent variable is the *level of* consensus recommendation and the *changes in* consensus recommendations, respectively. With a few exceptions, Table 7 confirms the univariate results reported in Table 6. Panel A shows that the level of the consensus recommendation is generally consistent with the Momentum variables, but runs counter to the Contrarian variables. Panel B shows that changes in the consensus recommendation are also consistent with the Momentum variables, but its correlation with the Contrarian variables is less clear.

The general picture that emerges from this 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 indicates 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 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. The relationship between recommendation *changes* and the contrarian investment signals is less clear, but we have some indication that analysts are less likely to contradict the contrarian signals when revising their recommendations. Evidently, recommendation *changes* are less prone to the growth bias observed in recommendation *levels*. At the same time, the relatively low correlation between recommendation *changes* and the other investment signals suggests that the former may have incremental predictive power relative to the investment 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 recommendation levels and changes. As before, 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 (see Appendix B). Panel A investigates the relation between RETF and recommendation levels quintiles (QCON). Panel B does the same for recommendation changes quintiles (QCHGCON).

Model A1 in Panel A is a univariate regression, with RETF as the dependent variable and QCON as the independent variables each quarter. The coefficient on QCON is positive and statistically significant in this regression, indicating that when used alone, this variable helps to predict future returns.

To assess whether QCON incrementally predicts returns when used in conjunction with the 12 characteristic-based signals, we consider several different regression specifications. In the first multivariate regression, we use Momentum and Contrarian Scores, in addition to QCON, as independent variables (Model A2). In this model, the QCON coefficient is not reliably different from zero. Therefore, analyst recommendation levels do not add incremental value relative to the other variables in this regression.

To assess whether the loss of significance of QCON is due to the Momentum or Contrarian score, we fit two other models. In model A3, QCON and Momentum score are the independent variables and in model A4 QCON and contrarian score are the independent variables. We find that QCON is not significant in A3 but is significant in A4. These results indicate that analyst recommendations predict returns mostly due to their momentum tilt. Recommendations do add value to a pure contrarian strategy, but only when the momentum signals are ignored.

Next, we consider a regression model where we use QCON and the 12 signals as separate independent variables (Model A5). This specification pits each of these signals against QCON individually rather than at an aggregated level. The slope coefficients on the investment signals can be interpreted as the six-month profits to a strategy that buys the stocks with a signal of 1 and sells the stocks with a signal of 0 for that variable, after controlling for the effects of the other signals. In our sample period, all the investment signals except SIZE and BP are correlated with future returns in the direction documented in the literature. However, only RETP, FREV, TA, and CAPEX, are significant in the multivariate regression. The statistical significance of the FREV and TA coefficients are particularly striking. The FREV and TA coefficients are positive in 48 and 52 out of the 56 quarters, respectively. These results indicate FREV and TA based trading strategies were consistently profitable in our sample period.

The QCON coefficient, however, is not statistically significant in this regression. This coefficient is positive in only 32 out of the 56 quarters. Collectively, the evidence from these regressions suggests that while QCON is weakly correlated with returns, its contribution is minor when considered in conjunction with the momentum signals. However, QCON may be at a handicap in these models because they allow the slope coefficients for the independent variables to take the “right'” sign in predicting returns.

Therefore, as a final test, we fit a regression where the independent variable that we use in addition to QCON is its fitted value (Qfitcon) from the regression in Table 7 Panel A (Model A6). Interestingly, QCON is not statistically significant in this regression, but Qfitcon is significant. This evidence also confirms the message from our earlier tests: the investment value of QCON is largely due to its tilt towards firm characteristics that are related to future returns.[16]

Our conclusions about the incremental value of the level of analyst recommendations differ from that in Barber et al. (2001a). Barber et al. (2001a) find that the abnormal returns to their analyst recommendations based strategy are significantly positive under the four-factor characteristic model proposed by Carhart (1997). The four-factor model includes a size factor, a book-to-market factor and a momentum factor, in addition to the market factor we consider in the CAPM model.

The main reason why our conclusions are different from that in Barber et al. (2001a) is that we are specifically interested in investigating the source of investment value for analyst recommendations, and hence we control for the effects of a broad set of stock characteristics. Among the twelve variables we consider, the momentum variables are the most important for explaining the value of analyst recommendations. Our models include two price momentum variables and two earnings momentum variables. As we discussed earlier, analysts significantly tilt their recommendations towards all four of our momentum variables. Chan et al. (1996) finds that each of the price and earnings momentum variables has incremental power to predict future returns, and none of these variables subsume the others.

The four-factor model, however, uses only the factor sensitivity to the momentum factor to control for momentum effect. Given the evidence in Chan et al (1996), it is unlikely that any single variable can capture the combined effects of price and earnings momentum. In fact, it is doubtful that the sensitivity to the momentum factor in the four-factor model even fully accounts for the price momentum effect. For instance, we find a strong monotonic relation between price momentum and analyst recommendations in Table 6. However, Barber et al. results indicate that the sensitivity of future returns to the momentum factor does not vary monotonically across recommendation quintiles. In fact, their middle portfolio has the highest sensitivity to the momentum factor, while we find that the most favorably recommended portfolio has the largest price momentum.

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[16] Lee and Swaminathan (2000) document a significant interaction between trading volume and price momentum in returns prediction. To evaluate this possibility, we repeated all these tests with the inclusion of a RETP*TURN interaction term. Our results are not sensitive to the inclusion of the interaction term in the regression.

Therefore, although a strategy based on analyst recommendations earns abnormal returns when the four-factor model is used as a benchmark, it does not have incremental value relative to a more comprehensive set of stock characteristics.

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 categories over the next six months. Next we consider multiple regressions with CHGCONS and the other independent variables that we earlier used with QCON. In the last regression specification (Model B6), we include the fitted value (Qfitchgcon) for QCHGCON from the regression in Table 7 as a control variable. Models B2 through B4 show that QCHGCON remains statistically significant when Momentum and Contrarian scores are (either individually or jointly) in the regressions. Model B5 indicates that QCHGCON is significant even when all 12 quantitative investment signals are separately included in the regression. Model B6 shows that QCHGCON is significant even with the inclusion of Qfitchgcon. These results consistently indicate that QCHGCONS is incrementally useful in predicting returns.[17]

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 section, we examine the performance of levels and changes of analyst recommendations within each category of stocks 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

[17] 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 little marginal predictive power even during our sample period.

change categories. For this panel, Worst (Best) firms are firms that are in both the lowest (highest) CONS and the lowest (highest) CHGCONS categories. 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 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 13.55% over the next six months.

The results along the right column of each panel show that analyst recommendations (CONS) have some limited predictive power after controlling for QScore, but that this power is conditional on the QScore category. Specifically, CONS is only useful among high QScore firms. In the highest QScore category, top CONS quintile firms earn 5.04% 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 -4.27%. 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 -9.51% (labeled "DISAGREE") is statistically significant at the 1% level. Evidently when the two signals are in conflict, 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 9.28% to 11.86% over the next six months. In all three panels, the combined strategy generates higher returns than those earned by considering either signal alone.

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 categories 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 groupings (BUY-SELL) and between the extreme CHGCONS groupings (INCREASE-DECREASE) within each of the QScore categories over 55 quarters. Panels B and C repeat the analyses for Momentum and Contrarian categories, respectively. 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. All Panels show that CHGCONS strategies generate positive returns over all holding periods and in all categories 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 overall is because it generates positive excess returns only in high QScore categories. In low QScore groups, 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, this pattern is observed within classifications based on both Momentum scores and Contrarian scores.

Figure 2 illustrates different roles played by CONS and CHGCONS in return prediction. These figures show the difference in mean returns between the extreme recommendation quintiles within each quantitative score category. Across the bottom of each figure is the holding period of the strategy. The darker bars correspond to the low quantitative score categories (QScore, Momentum, and Contrarian), the lighter bars correspond to the high summary quantitative score categories.

Panel A shows that the CONS strategy yields positive returns for the high quantitative score categories (lighter bars), but the same strategy yields negative returns for the low quantitative score categories (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) categories. 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 categories, 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, although they are not statistically significant in several instances. 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 much of the predictive power of analyst stock recommendations derives from their correlation with the other explanatory variables. The usefulness of the consensus level measure (QCON) depends on the quantitative investment signal. Specifically, QCON is a useful predictor of returns only when it confirms already favorable quantitative signals. The usefulness of QCHGCON for returns prediction is more robust, and is incremental to that of 12 other variables.

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 high momentum stocks and growth stocks. 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.

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. For example, 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 and recommendation changes 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 and the relatively small magnitude of price run-ups, it would be difficult to distinguish this scenario from the one in which analysts are facilitating the price formation process.

Our results suggest that financial analysts may be able to improve their stock recommendations by paying more attention to the relation between stock characteristics and future 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' goal is to generate recommendations with greater predictive power for returns, they should more favorably recommendation firms with lower trading volume, higher EP ratios, lower LTG and SG measures, more negative (income decreasing) accruals, and lower capital expenditures.[18]

[18] 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)).

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 entirely 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 claims of some pundits in popular press (e.g., Der Hovanesian (2001)), the level of the analyst recommendation 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 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 trades driven by the level of sell-side analyst recommendations is an example of such noise trading.

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APPENDIX A: Investment Signals

This appendix provides a detailed description of the twelve investment signals used in the study. All these explanatory variables were winsorized 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)	$\{[\Pi_{i=m-6}^{m-1}(1+\text{monthlyreturn}_i)]-1\}$ $-\{[\Pi_{i=m-6}^{m-1}(1+\text{value-weighted marketmonthlyreturn}_i)]-1\}$, where m = month-end of quarter t *[CRSP]*
2. RET2P	Cumulative market-adjusted return for the second preceding six months (months –12 through –7)	$\{[\Pi_{i=m-12}^{m-7}(1+\text{monthlyreturn}_i)]-1\}$ $-\{[\Pi_{i=m-12}^{m-7}(1+\text{value-weighted marketmonthlyreturn}_i)]-1\}$, 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)	$Size_t = LN(P_{,t} * \text{Shares Outstanding}_t)$ = 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	$\frac{(EPS_q - EPS_{q-4})}{s_q}$, 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 A: 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)	$\frac{\left\{ \begin{array}{l} (\Delta\text{Current Assets}_q\ [D40] - \Delta\text{Cash}_q\ [D36]) \\ -(\Delta\text{Current Liabilities}_q\ [D49] - \Delta\text{Current LTD}_q\ [D45]) \\ -\ \Delta\text{Deferred taxes}_q\ [D35] \\ -\ \text{Depreciation and amortization}_q\ [D5] \end{array} \right\}}{(\text{TA}_q + \text{TA}_{q-4})/2\ [D44]}$, 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-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_t = 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 A: 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.

APPENDIX B: Computation of Autocorrelation-consistent Test Statistics

This appendix describes the computation of autocorrelation-consistent test statistics used in various tables. In general, we obtain estimates separately for each quarter and report the time-series mean of these estimates in the tables. Specifically, we compute the mean $\bar{x}$ for the statistic of interest as:

$$\bar{x} = \sum_{t=1}^{T} x_t,$$

where T is the number of quarters in the sample period, and x_t is the estimate for quarter t. We compute the autocorrelation-consistent variance of $\bar{x}$ as:

$$Var(\bar{x}) = \frac{1}{T^2}\left(T \times Var(x_t) + 2\sum_{k=1}^{K} (T-k) SCOV_k(x_t)\right),$$

where, Var is the variance, and $SCOV_k$ is the k^{th}-order serial covariance, and K is the number of non-zero serial covariances. We use the sample estimates of the variances and serial covariances from the time-series estimates of x_t in the above expression. We use autocorrelation-consistent statistics in the following tables:

Table 3: We first compute the correlation coefficients (Panel A) and six-month holding period returns (Panels B and C) every quarter. The table reports the mean values. Since the overlap in adjacent six-month return measurement intervals is one quarter, we set $K=1$.

Tables 4 and 5: We follow the same procedure as for Table 3.

Table 7: We estimate the regressions separately for each quarter. Since the recommendation levels are fairly stable, we allow for correlation in regression estimates over four quarters, i.e. we set $K=4$.

Table 8: We estimate the regressions separately for each quarter. Since the overlap in adjacent six-month return measurement intervals is one quarter, we set $K=1$.

Table 9: Same as Table 3.

Table 10: We compute holding period returns every quarter. We set $K=0$ for one- and three-month holding periods, $K=1$ for six-month holding periods, $K=2$ for nine-month holding periods, and $K=3$ for 12-month holding periods.

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 Compustat and IBES information. Exchange listing is obtained at the time of the consensus recommendation.

PANEL A: Year

Year	Mean Obs per Quarter	Sample %age per Year	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
Mean quarterly 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%
Mean quarterly sample	971.43	100.0%

PANEL C: NYSE Size Decile

NYSE Mkt Cap Decile	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)	13.79	1.3%	73.16	7.8%	86.95	9.0%
9	25.82	2.4%	64.38	6.9%	90.20	9.3%
8	35.98	3.4%	52.98	5.7%	88.96	9.1%
7	42.98	4.3%	45.04	4.9%	88.02	9.1%
6	48.34	4.8%	38.77	4.2%	87.11	8.9%
5	59.25	6.1%	34.02	3.7%	93.27	9.8%
4	64.14	6.5%	30.38	3.4%	94.52	9.9%
3	78.16	7.7%	28.16	3.2%	106.32	11.0%
2	87.95	8.7%	20.04	2.3%	107.98	10.9%
1 (Smallest)	113.25	11.3%	14.86	1.6%	128.11	12.8%
Mean quarterly sample	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, Compustat, and IBES 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. Our unit of observation in Panels A and B is the firm-quarter. Our estimates are formed once each quarter, in cross-section. We aggregate these quarterly estimates and report the time-series averages. 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
Mean of 56 quarterly samples		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
Mean of 55 quarterly samples		974.46	–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). Our unit of observation is the firm-quarter. Our estimates are formed once each quarter, in cross-section. We aggregate these quarterly estimates and report the time-series averages of these cross-sectional tests. ***, **, * 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 autocorrelation consistent standard errors (as described in Appendix B).

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 Appendix A. 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). Our unit of observation is the firm-quarter. Our estimates are formed once each quarter, in cross-section. We aggregate these quarterly estimates and report the time-series averages of these cross-sectional tests. ***, **, * indicates two–sided statistical significance at 1%, 5%, and 10%, respectively, based on t–statistics calculated with autocorrelation consistent standard errors (as described in Appendix B). The positive portfolio returns indicates the percentage of the 56 quarters in which the net portfolio return was above 0%.

Explanatory Variable	Continuous Explanatory Variable Correlation	Binary Explanatory Variable				
		Normative 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 ***	43 of 56 76.79%
RET2P	+0.043 ***	*1 if greater than median 0 otherwise*	50.01%	+0.039 ***	+0.013 *	35 of 56 62.50%
TURN	–0.034 **	*1 if less than median 0 otherwise*	50.24%	+0.033 **	+0.002	35 of 56 62.50%
SIZE	+0.088 ***	*1 if less than median 0 otherwise*	49.98%	–0.077 ***	–0.016	20 of 56 35.71%
FREV	+0.099 ***	*1 if greater than median 0 otherwise*	49.99%	+0.091 ***	+0.042 ***	47 of 56 83.93%
LTG	–0.006	*1 if less than median 0 otherwise*	50.00%	+0.008	–0.000	30 of 56 53.57%
SUE	+0.053 ***	*1 if greater than median 0 otherwise*	50.00%	+0.040 ***	+0.018 **	38 of 56 67.86%
SG	–0.025 *	*1 if less than median 0 otherwise*	49.99%	+0.025 *	+0.004	32 of 56 57.14%
TA	–0.081 ***	*1 if less than median 0 otherwise*	50.01%	+0.063 ***	+0.029 ***	48 of 56 85.71%
CAPEX	–0.021 *	*1 if less than median 0 otherwise*	50.01%	+0.023 **	+0.015 ***	39 of 56 69.64%
BP	–0.016	*1 if greater than median 0 otherwise*	50.02%	–0.010	–0.000	28 of 56 50.00%
EP	+0.038 **	*1 if greater than median 0 otherwise*	49.96%	+0.029 **	+0.004	31 of 56 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 seven contrarian signals: EP, BP, TURN, LTG, SG, TA, CAPEX), and QScore (the sum of all 12 investment signals, including SIZE). Each individual signal is described in detail in Appendix A. We combine extreme categories of the summary variables, such that extreme groups have an average of at least 100 stocks per quarter. Panel A reports the Spearman rank correlation between each sum measure and future returns. Panel B reports future returns grouped by QScore categories, Panel C reports future returns grouped by Momentum categories, and Panel D reports future returns for firms grouped by Contrarian categories. Our unit of observation is the firm-quarter. Our estimates are formed once each quarter, in cross-section. We aggregate these quarterly estimates and report the time-series averages of these cross-sectional tests. ***, **, * 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 autocorrelation consistent standard errors (see Appendix B).

PANEL A: Spearman Rank Correlations with Future Returns

Explanatory Variable	Mean	Median
QScore	0.0830 ***	0.0850 ***
Momentum	0.0865 ***	0.0907 ***
Contrarian	0.0488 ***	0.0539 ***

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

FScore Sum	Coded as	Mean Obs per Qtr	Mean	Median
Best = 9, 10, 11, 12	1.00	103.96	+0.0194	–0.0060
8	0.83	116.36	–0.0025	–0.0236
7	0.67	162.71	–0.0080	–0.0284
6	0.50	181.16	–0.0097	–0.0356
5	0.33	171.36	–0.0263	–0.0420
4	0.17	118.93	–0.0334	–0.0566
Worst = 0, 1, 2, 3	0.00	99.46	–0.0506	–0.0760
Best – Worst			+0.0699 ***	+0.0685 ***

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

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* Category

Contrarian Sum	Coded as	Mean Obs per Qtr	Mean	Median
Best = 6, 7	1.00	113.50	+0.0032	-0.0200
5	0.80	173.45	-0.0094	-0.0318
4	0.60	206.77	-0.0176	-0.0426
3	0.40	188.07	-0.0194	-0.0451
2	0.20	145.05	-0.0161	-0.0417
Worst = 0, 1	0.00	127.11	-0.0278	-0.0444
Best – Worst			+0.0310 **	+0.0274 **

TABLE 6: Descriptive Statistics by Consensus Recommendation Quintile

This table exa mines the relation between the level of the consensus recommendation and twelve investment signals. The signals are described in detail in Appendix A. Our unit of observation is the firm-quarter. Our estimates are formed once each quarter, in cross-section. We aggregate these quarterly estimates and report the time -series averages. To construct Panel A, we sort all firms into quintiles in each quarter by the level of their consensus stock recommendation. Table values represent the mean 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. Correlation is the mean Spearman rank correlation between the consensus recommendation and a given investment signal across the quarters. Actual Direction indicates the sign of the relation when the rank correlation is 10% or higher . In Panel B, we repeat this analysis for changes in consensus recommendations, across the 55 available quarters.

PANEL A: Consensus Recommendation Levels

Continuous Explanatory Variable		Normative Direction	Consensus Recommendation Quintile BUY 1.00	0.75	0.50	0.25	SELL 0.00	Correlation	Actual Direction
SIZE	Mean	-	5.5629	6.1999	6.4940	6.2727	5.2186	4.29%	?
Momentum Variables (Price or Earning)									
RETP	Mean	+	0.1508	0.1192	0.0827	0.0277	-0.0241	26.89%	+
RET2P	Mean	+	0.1758	0.1384	0.0946	0.0430	-0.0146	27.90%	+
FREV	Mean	+	-0.3274	-0.4703	-0.7619	-1.4352	-2.6510	34.59%	+
SUE	Mean	+	1.0068	0.8898	0.5319	0.1230	-0.2711	32.10%	+
Contrarian Variables (Fundamental or Growth)									
EP	Mean	+	0.0580	0.0551	0.0543	0.0465	0.0262	11.89%	+
BP	Mean	+	0.4727	0.4832	0.5281	0.5996	0.7499	-30.11%	-
TURN	Mean	-	52.2900	53.1011	52.5706	50.0011	41.1517	11.82%	+
SG	Mean	-	1.2203	1.1875	1.1356	1.1032	1.0728	29.64%	+
LTG	Mean	-	24.0312	20.1197	14.4616	9.7340	3.4313	27.24%	+
TA	Mean	-	0.0213	0.0148	0.0052	0.0025	0.0018	10.62%	+
CAPEX	Mean	-	0.0887	0.0901	0.0897	0.0872	0.0766	4.24%	?

PANEL B: Consensus Recommendation Changes

Continuous Explanatory Variable		Normative Direction	Consensus Recommendation Quintile BUY 1.00	0.75	0.50	0.25	SELL 0.00	Correlation	Actual Direction
SIZE	Mean	-	5.8730	6.9277	5.0580	6.9500	5.8029	0.96%	?
Momentum Variables (Price or Earning)									
RETP	Mean	+	0.1111	0.0994	0.0576	0.0665	0.0137	14.58%	+
RET2P	Mean	+	0.0706	0.0979	0.0705	0.0954	0.0967	-3.24%	?
FREV	Mean	+	-0.9649	-0.7163	-1.3829	-0.9096	-1.5472	9.73%	?
SUE	Mean	+	0.3958	0.6120	0.3033	0.6220	0.3596	1.42%	?
Contrarian Variables (Fundamental or Growth)									
EP	Mean	+	0.0428	0.0484	0.0440	0.0500	0.0511	-3.93%	?
BP	Mean	+	0.5819	0.4985	0.6440	0.4896	0.5554	3.00%	?
TURN	Mean	-	49.5835	56.8875	40.2862	56.8940	52.5123	-3.14%	?
SG	Mean	-	1.1309	1.1444	1.1303	1.1500	1.1600	-5.16%	?
LTG	Mean	-	12.6934	15.3931	10.9226	16.4032	17.3849	-5.76%	?
TA	Mean	-	0.0052	0.0038	0.0105	0.0058	0.0161	-5.30%	?
CAPEX	Mean	-	0.0848	0.0908	0.0786	0.0924	0.0895	-2.25%	?

TABLE 7: Regression of Recommendations on Explanatory Variables

This table reports the result when analyst recommendation metrics are regressed on various continuous 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 Appendix A. For ease of interpretation, the explanatory variables have been standardized by their mean and standard deviation for each quarter. Our unit of observation is the firm-quarter. Our estimates are formed once each quarter, in cross-section. We aggregate these quarterly estimates and report the time-series averages of these cross-sectional tests. ***, **, * indicates two–sided statistical significance at 1%, 5%, and 10%, respectively, based on t–statistics calculated with autocorrelation consistent standard errors (as described in Appendix B).

PANEL A: Consensus Recommendation Levels ("CONS")

Mean R^2 25.70%
Mean F statistic 27.53

VARIABLE	NORM	ACTUAL	Mean $\hat{b}$	t
Intercept			+3.670	+71.29 ***
SIZE	–	+	–0.070	–3.72 ***
Momentum Variables (Price or Earning)				
RETP	+	+	+0.101	+15.16 ***
RET2P	+	+	+0.074	+10.08 ***
FREV	+	+	+0.077	+11.45 ***
SUE	+	+	+0.061	+7.90 ***
Contrarian Variables (Fundamental or Growth)				
EP	+	+	+0.041	+6.57 ***
BP	+	–	–0.097	–17.63 ***
TURN	–	?	+0.042	+8.21 ***
LTG	–	+	+0.056	+6.05 ***
SG	–	+	+0.051	+5.98 ***
TA	–	+	+0.017	+3.86 ***
CAPEX	–	?	+0.009	+2.00 **

PANEL B: Consensus Recommendation Changes ("CHGCONS")

Mean R^2 14.88%
Mean F statistic 12.43

VARIABLE	NORM	ACTUAL	Mean $\hat{b}$	t
Intercept			+0.197	+11.90 ***
Prior consensus quintile			–0.431	–13.88 ***
SIZE	–	?	–0.002	–0.32
Momentum Variables (Price or Earning)				
RETP6	+	+	+0.061	+10.26 ***
RET2P6	+	?	+0.003	+0.65
FREV	+	?	+0.043	+12.04 ***
SUE	+	?	+0.012	+4.89 ***
Contrarian Variables (Fundamental or Growth)				
EP	+	?	–0.013	–4.08 ***
BP	+	?	–0.007	–2.17 **
TURN	–	?	+0.001	+0.83
LTG	–	?	+0.009	+3.41 ***
SG	–	?	+0.008	+5.19 ***
TA	–	?	–0.002	–1.07
CAPEX	–	?	+0.001	+0.59

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 are the quintile of the consensus recommendation level (QCON), and the quintile of the change in the consensus measured over the prior quarter (QCHGCON). Two different summary variables are used: Momentum (the sum of four momentum signals: RETP, RET2P, FREV, SUE) and Contrarian (the sum of seven contrarian signals: EP, BP, TURN, LTG, SG, TA, CAPEX), as described in Table 5. QFITCON and QFITCHGCON are fitted values of QCON and QCHGCON from Panels A and B of Table 7, respectively. Our unit of observation is the firm-quarter. Our estimates are formed once each quarter, in cross-section. We aggregate these quarterly estimates and report the time-series averages of these cross-sectional tests. ***, **, * indicates two–sided statistical significance at 1%, 5%, and 10%, respectively, based on t–statistics calculated with autocorrelation consistent standard errors (see Appendix B).

PANEL A: Consensus Recommendation Levels Quintiles (QCON)

	Model A1 *Analysts Alone*		**Model A2** *Analysts & **Both** Summary Variables*		**Model A3** *Analysts & **Momentum** Summary Variable*		**Model A4** *Analysts & **Contrarian** Summary Variable*		**Model A5** *Analysts & Binary Investment Signals*		**Model A6** *Analysts & Fitted Value*	
Parameter	**Estimate**	**t-stat**	**Estimate**	**t-stat**	**Estimate**	**t-stat**	**Estimate**	**t-stat**	**Estimate**	**t-stat**	**Estimate**	**t-stat**
Intercept	–0.0257	–2.52**	–0.0702	-4.86***	–0.0440	-3.34***	–0.0467	-3.43***	–0.0684	–4.90***	–0.0336	–2.72***
QCON	+0.0226	2.03**	+0.0088	1.07	+0.0009	0.10	+0.0310	2.95***	+0.0076	1.05	+0.0074	1.04
Momentum			+0.0619	5.27***	+0.0570	4.77***						
Contrarian			+0.0396	2.72***			+0.0336	2.29**				
SIZE									–0.0078	–0.93		
RETP									+0.0175	3.45***		
RET2P									+0.0019	0.36		
FREV									+0.0324	8.63***		
SUE									+0.0017	0.40		
EP									+0.0021	0.35		
BP									+0.0089	1.60		
TURN									+0.0011	0.15		
LTG									+0.0007	0.13		
SG									+0.0007	0.14		
TA									+0.0268	8.43***		
CAPEX									+0.0134	3.05***		
QFITCON											+0.0300	2.32**

TABLE 8: Future Returns, Analyst Recommendations, and Investment Signals (Continued)

PANEL B: Consensus Recommendation Changes Quintiles (QCHGCON)

	Model B1 *Analysts Alone*		**Model B2** *Analysts & **Both** Summary Variables*		**Model B3** *Analysts & **Momentum** Summary Variable*		**Model B4** *Analysts & **Contrarian** Summary Variable*		**Model B5** *Analysts & Binary Investment Signals*		**Model B6** *Analysts & Fitted Value*	
Parameter	**Estimate**	**t-stat**	**Estimate**	**t-stat**	**Estimate**	**t-stat**	**Estimate**	**t-stat**	**Estimate**	**t-stat**	**Estimate**	**t-stat**
Intercept	–0.0262	–2.67***	–0.0727	-5.00***	–0.0542	-3.88***	–0.0370	-3.14***	–0.0705	–5.07***	–0.0316	–2.83***
QCHGCON	+0.0225	4.84***	+0.0187	4.49***	+0.0205	4.74***	+0.0219	4.84***	+0.0159	4.24***	+0.0173	3.82***
Momentum			+0.0616	4.85***	+0.0544	4.05***						
Contrarian			+0.0349	2.43**			+0.0220	1.46				
SIZE									–0.0065	–0.76		
RETP									+0.0176	3.31***		
RET2P									+0.0014	0.26		
FREV									+0.0319	7.80***		
SUE									+0.0027	0.66		
EP									+0.0011	0.19		
BP									+0.0080	1.40		
TURN									+0.0000	0.00		
LTG									–0.0004	–0.07		
SG									+0.0002	0.04		
TA									+0.0261	8.24***		
CAPEX									+0.0132	2.91***		
QFITCHGCON											+0.0159	2.20**

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. Our unit of observation is the firm-quarter. Our estimates are formed once each quarter, in cross-section. We aggregate these quarterly estimates and report the time-series averages of these cross-sectional tests. ***, **, * indicates two–sided statistical significance at 1%, 5%, and 10%, respectively, based on t–statistics calculated with autocorrelation consistent standard errors (as described in Appendix B).

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**	18.33	–0.0482	23.58	–0.0327	22.67	–0.0302	22.15	–0.0605	14.36	–0.0909	–0.0427	–2.01	**
	0.17	23.04	–0.0401	24.18	–0.0321	26.82	–0.0154	25.24	–0.0332	21.38	–0.0312	+0.0090	+0.45	
	0.33	37.44	–0.0394	33.87	–0.0254	35.62	–0.0279	36.53	–0.0168	30.55	–0.0155	+0.0239	+1.58	
	0.50	41.62	–0.0274	35.71	–0.0026	35.29	–0.0043	36.96	–0.0046	33.95	+0.0006	+0.0279	+1.86	*
	0.67	37.78	–0.0223	28.89	–0.0216	34.69	–0.0013	32.73	+0.0015	30.96	+0.0069	+0.0291	+1.95	*
	0.83	27.02	–0.0036	21.31	–0.0130	23.93	–0.0163	22.24	+0.0154	23.67	+0.0048	+0.0085	+0.67	
Best=HIGH	**1.00**	24.22	+0.0041	17.52	–0.0032	21.62	–0.0053	19.58	+0.0313	23.00	+0.0445	+0.0504	+4.12	***
HIGH–LOW			+0.0524		+0.0271		+0.0249		+0.0918		+0.1355			
t			+3.04		+1.89		+1.53		+4.64		+8.82			
p			***		*				***		***			
Overall analysts' level recommendations = Buy – Sell (*see also Table 3 Panel B*)												+0.0216	+1.86	*
Overall quantitative strategy = High – Low (*see also Table 5 Panel B*)												+0.0677	+5.43	***
DISAGREE = Low&Buy–High&Sell												–0.0951	–5.14	***
AGREE = High&Buy–Low&Sell												+0.0928	+4.51	***

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

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**	27.89	–0.0688	21.04	–0.0184	18.05	–0.0733	17.38	–0.0406	16.16	–0.0402	+0.0286	+2.10	**
	0.17	27.45	–0.0478	22.80	–0.0222	26.49	–0.0585	21.13	–0.0179	21.87	–0.0080	+0.0398	+3.15	***
	0.33	37.45	–0.0393	29.75	–0.0106	44.11	–0.0373	28.75	–0.0068	32.25	–0.0248	+0.0145	+1.61	
	0.50	36.55	–0.0189	26.16	+0.0051	54.56	–0.0203	27.80	–0.0020	36.49	–0.0007	+0.0182	+1.83	*
	0.67	28.93	–0.0223	21.25	–0.0088	54.25	–0.0175	22.91	+0.0079	35.62	–0.0011	+0.0212	+2.03	**
	0.83	19.33	–0.0053	13.74	+0.0342	44.67	–0.0122	14.73	–0.0045	24.04	+0.0025	+0.0078	+0.52	
Best=HIGH	**1.00**	14.89	+0.0030	8.67	+0.0167	46.80	+0.0165	10.18	+0.0122	22.93	+0.0323	+0.0294	+2.14	**
HIGH–LOW			+0.0718		+0.0351		+0.0897		+0.0527		+0.0725			
t			+3.84		+1.61		+5.65		+3.62		+4.59			
p			***				***		***		***			
Overall Analysts’ change recommendations = Incr–Decr (*see also Table 3 Panel C*)												+0.0268	+5.81	***
Overall Quantitative strategy = High–Low (*see also Table 5 Panel B*)												+0.0677	+5.43	***
DISAGREE = Low&Incr–High&Decr												–0.0432	–2.11	**
AGREE = High&Incr–Low&Decr												+0.1011	+7.19	***

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				
Qscore Quintile		Obs	Mean	Obs	Mean	Obs	Mean	BUY&INCR - SELL&DECR	*t*	*p*
Worst=LOW	**0.00**	7.47	–0.0757	89.56	–0.0459	4.05	–0.0559	+0.0198	+0.62	
	0.17	8.80	–0.0717	106.20	–0.0304	5.87	+0.0070	+0.0767	+2.42	**
	0.33	12.58	–0.0591	153.56	–0.0235	7.85	–0.0290	+0.0302	+1.33	
	0.50	12.20	–0.0359	161.55	–0.0093	9.78	+0.0092	+0.0451	+2.34	**
	0.67	9.75	–0.0497	146.42	–0.0080	8.89	+0.0143	+0.0640	+2.95	***
	0.83	6.38	+0.0035	104.95	–0.0062	6.84	+0.0127	+0.0039	+0.11	
Best=HIGH	**1.00**	4.49	+0.0142	94.67	+0.0172	6.62	+0.0429	+0.0328	+0.71	
HIGH–LOW			+0.0905		+0.0631		+0.0978			
t			+1.79		+4.89		+3.28			
p			*		***		***			
Overall analysts’ combined recommendations = Buy&Incr–Sell&Decr								+0.0529	+4.19	***
Overall quantitative strategy = High–Low (*see also Table 5 Panel B*)								+0.0677	+5.43	***
DISAGREE = Low&(Buy&Incr)–High&(Sell&Decr)								–0.0668	–1.29	
AGREE = High&(Buy&Incr)–Low&(Sell&Decr)								+0.1186	+4.00	***

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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. Our unit of observation is the firm-quarter. Our estimates are formed once each quarter, in cross-section. We aggregate these quarterly estimates and report the time-series averages of these cross-sectional tests. ***, **, * indicates two–sided statistical significance at 1%, 5%, and 10%, respectively, based on t–statistics calculated with autocorrelation consistent standard errors (as described in Appendix B).

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**	18.04	–0.0485	23.21	–0.0358	22.30	–0.0321	21.80	–0.0613	14.36	–0.0909	–0.0427	-2.01**
	0.17	22.75	–0.0438	23.88	–0.0325	26.82	–0.0154	24.96	–0.0337	21.38	–0.0312	+0.0090	0.45
	0.33	36.86	–0.0393	33.41	–0.0259	35.04	–0.0287	36.05	–0.0178	30.55	–0.0155	+0.0239	1.58
	0.50	41.13	–0.0271	35.46	–0.0027	34.68	–0.0062	36.48	–0.0033	33.41	–0.0013	+0.0258	1.75*
	0.67	37.23	–0.0216	28.55	–0.0206	34.13	–0.0016	32.36	+0.0021	30.45	+0.0106	+0.0321	2.16**
	0.83	26.57	–0.0022	20.98	–0.0138	23.52	–0.0183	21.98	+0.0146	23.30	+0.0072	+0.0095	0.75
Best=HIGH	**1.00**	24.22	+0.0041	17.35	–0.0034	21.25	–0.0042	19.29	+0.0340	22.61	+0.0491	+0.0504	4.12***
HIGH–LOW			+0.0524		+0.0301		+0.0279		+0.0953		+0.1355		
t			3.04		2.05		1.73		4.77		8.82		
p			***		**		*		***		***		
Overall analysts' level recommendations = Buy–Sell (*see also Table 3 Panel B*)												+0.0234	2.04**
Overall quantitative strategy = High–Low (*see also Table 5 Panel B*)												+0.0699	5.54***
DISAGREE = Low&Buy–High&Sell												–0.0951	-5.14***
AGREE = High&Buy–Low&Sell												+0.0976	4.78***

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

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	27.89	–0.0688	21.04	–0.0184	18.05	–0.0733	17.38	–0.0406	16.16	–0.0402	+0.0286	+2.10	**
	0.17	27.45	–0.0478	22.80	–0.0222	26.49	–0.0585	21.13	–0.0179	21.87	–0.0080	+0.0398	+3.15	***
	0.33	37.45	–0.0393	29.75	–0.0106	44.11	–0.0373	28.75	–0.0068	32.25	–0.0248	+0.0145	+1.61	
	0.50	36.55	–0.0189	26.16	+0.0051	54.56	–0.0203	27.80	–0.0020	36.49	–0.0007	+0.0182	+1.83	*
	0.67	28.93	–0.0223	21.25	–0.0088	54.25	–0.0175	22.91	+0.0079	35.62	–0.0011	+0.0212	+2.03	**
	0.83	19.33	–0.0053	13.74	+0.0342	44.67	–0.0122	14.73	–0.0045	24.04	+0.0025	+0.0078	+0.52	
Best=HIGH	1.00	14.89	+0.0030	8.67	+0.0167	46.80	+0.0165	10.18	+0.0122	22.93	+0.0323	+0.0294	+2.14	**
HIGH–LOW			+0.0718		+0.0351		+0.0897		+0.0527		+0.0725			
t			+3.84		+1.61		+5.65		+3.62		+4.59			
p			***				***		***		***			
Overall Analysts' change recommendations = Incr–Decr (*see also Table 3 Panel C*)												+0.0268	+5.81	***
Overall Quantitative strategy = High–Low (*Comparable to Table 5 Panel B, excluding first quarter*)												+0.0677	+5.43	***
DISAGREE = Low&Incr–High&Decr												–0.0432	–2.11	**
AGREE = High&Incr–Low&Decr												+0.1011	+7.19	***

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				
Qscore Quintile		Obs	Mean	Obs	Mean	Obs	Mean	BUY&INCR - SELL&DECR	*t*	*p*
Worst=LOW	0.00	7.47	–0.0757	89.56	–0.0459	4.05	–0.0559	+0.0198	+0.62	
	0.17	8.80	–0.0717	106.20	–0.0304	5.87	+0.0070	+0.0767	+2.42	**
	0.33	12.58	–0.0591	153.56	–0.0235	7.85	–0.0290	+0.0302	+1.33	
	0.50	12.20	–0.0359	161.55	–0.0093	9.78	+0.0092	+0.0451	+2.34	**
	0.67	9.75	–0.0497	146.42	–0.0080	8.89	+0.0143	+0.0640	+2.95	***
	0.83	6.38	+0.0035	104.95	–0.0062	6.84	+0.0127	+0.0039	+0.11	
Best=HIGH	1.00	4.49	+0.0142	94.67	+0.0172	6.62	+0.0429	+0.0328	+0.71	
HIGH–LOW			+0.0905		+0.0631		+0.0978			
t			+1.79		+4.89		+3.28			
p			*		***		***			
Overall analysts' combined recommendations = Buy&Incr–Sell&Decr								+0.0529	+4.19	***
Overall quantitative strategy = High–Low (*Comparable to Table 5 Panel B, excluding first quarter*)								+0.0677	+5.43	***
DISAGREE = Low&(Buy&Incr)–High&(Sell&Decr)								–0.0668	–1.29	
AGREE = High&(Buy&Incr)–Low&(Sell&Decr)								+0.1186	+4.00	***

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) and changes quintiles (INCREASE-DECREASE) within each of the QScore categories. Panels B and C repeat the analyses for Momentum and Contrarian categories, respectively. Our unit of observation is the firm-quarter. Our estimates are formed once each quarter, in cross-section. We aggregate these quarterly estimates and report the time-series averages of these cross-sectional tests. ***, **, * indicates two–sided statistical significance at 1%, 5%, and 10%, respectively, based on t–statistics calculated with autocorrelation consistent standard errors (see Appendix B).

PANEL A: Mean market–adjusted return difference within each *QScore* category

Holding Period	Worst=LOW: 0.00	0.17	0.33	0.50	0.67	0.83	Best=HIGH: 1.00
Extreme recommendation *levels* (BUY–SELL) within QScore Category							
1 month	–0.0118	+0.0073	–0.0044	+0.0120 **	+0.0058	+0.0032	+0.0087 **
3 months	–0.0219 **	+0.0096	+0.0174 *	+0.0126	+0.0205 **	+0.0227 **	+0.0298 ***
6 months	–0.0427 **	+0.0090	+0.0239	+0.0279 *	+0.0291 *	+0.0085	+0.0504 ***
9 months	–0.0740 **	–0.0067	+0.0146	+0.0369 *	+0.0209	+0.0182	+0.0628 ***
12 months	–0.0963 **	–0.0131	+0.0193	+0.0258	+0.0195	+0.0011	+0.0560 ***
Extreme *changes* (INCREASE–DECREASE) within QScore Category							
1 month	+0.0053	+0.0108 **	+0.0061	+0.0082 **	+0.0104 ***	+0.0036	+0.0128 ***
3 months	+0.0066	+0.0191 **	+0.0111 *	+0.0133 *	+0.0168 ***	+0.0133	+0.0189 **
6 months	+0.0286 **	+0.0398 ***	+0.0145	+0.0182 *	+0.0212 **	+0.0078	+0.0294 **
9 months	+0.0240	+0.0360 ***	+0.0155	+0.0375 ***	+0.0333 *	+0.0101	+0.0452 ***
12 months	+0.0210	+0.0369 **	+0.0099	+0.0326 **	+0.0289	+0.0194	+0.0722 ***

PANEL B: Mean market–adjusted return difference within each *Momentum* category

Holding Period	Worst=LOW: 0.00	0.25	0.50	0.75	Best=HIGH: 1.00
Extreme recommendation *levels* (BUY–SELL) within Momentum Category					
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
Extreme *changes* (INCREASE–DECREASE) within Momentum Category					
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 ***

PANEL C: Mean market–adjusted return difference within each *Contrarian* category

Holding Period	Worst=LOW: 0.00	0.20	0.40	0.60	0.80	Best=HIGH: 1.00
Extreme recommendation *levels* (BUY–SELL) within Contrarian Category						
1 month	+0.0064	+0.0111 *	+0.0025	+0.0069	+0.0104 **	+0.0046
3 months	+0.0126	+0.0233 *	+0.0123	+0.0238 ***	+0.0271 ***	+0.0302 ***
6 months	+0.0046	+0.0345 *	+0.0180	+0.0362 ***	+0.0306 **	+0.0580 ***
9 months	–0.0403	+0.0366	+0.0266	+0.0408 **	+0.0368 **	+0.0670 ***
12 months	–0.0524	+0.0373	+0.0272	+0.0429 **	+0.0248	+0.0632 **
Extreme *changes* (INCREASE–DECREASE) within Contrarian Category						
1 month	+0.0114 **	+0.0067	+0.0081 ***	+0.0112 ***	+0.0106 **	+0.0092 **
3 months	+0.0156 *	+0.0117	+0.0194 ***	+0.0143 **	+0.0228 ***	+0.0117
6 months	+0.0422 ***	+0.0230 **	+0.0174 **	+0.0267 ***	+0.0274 ***	+0.0190
9 months	+0.0418 ***	+0.0264	+0.0296 ***	+0.0282 **	+0.0367 ***	+0.0417 **
12 months	+0.0405 ***	+0.0167	+0.0303 **	+0.0282 *	+0.0418 **	+0.0433

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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) and changes quintiles (INCREASE-DECREASE) within each of the QScore categories. Panels B and C repeat the analyses for Momentum and Contrarian categories, respectively. Our unit of observation is the firm-quarter. Our estimates are formed once each quarter, in cross-section. We aggregate these quarterly estimates and report the time-series averages of these cross-sectional tests. ***, **, * indicates two–sided statistical significance at 1%, 5%, and 10%, respectively, based on t–statistics calculated with autocorrelation consistent standard errors (see Appendix B).

PANEL A: Mean market–adjusted return difference within each *QScore* category

Holding Period	Worst=LOW: 0.00	0.17	0.33	0.50	0.67	0.83	Best=HIGH: 1.00
Extreme recommendation *levels* (BUY–SELL) within QScore Category							
1 month	–0.0118	+0.0073	–0.0044	+0.0115	+0.0085	+0.0047	+0.0087
3 months	–0.0219	+0.0096	+0.0174	+0.0113	+0.0240	+0.0263	+0.0298
6 months	–0.0427 **	+0.0090	+0.0239	+0.0258 *	+0.0321 **	+0.0095	+0.0504 ***
9 months	–0.0740 **	–0.0067	+0.0146	+0.0363 *	+0.0278 *	+0.0190	+0.0628 ***
12 months	–0.0963 **	–0.0131	+0.0193	+0.0266	+0.0307	+0.0045	+0.0560 ***
Extreme *changes* (INCREASE–DECREASE) within QScore Category							
1 month	+0.0053	+0.0108 **	+0.0061	+0.0082 **	+0.0104 ***	+0.0036	+0.0128 ***
3 months	+0.0066	+0.0191 **	+0.0111 *	+0.0133 *	+0.0168 ***	+0.0133	+0.0189 **
6 months	+0.0286 **	+0.0398 ***	+0.0145	+0.0182 *	+0.0212 **	+0.0078	+0.0294 **
9 months	+0.0240	+0.0360 ***	+0.0155	+0.0375 ***	+0.0333 *	+0.0101	+0.0452 ***
12 months	+0.0210	+0.0369 **	+0.0099	+0.0326 **	+0.0289	+0.0194	+0.0722 ***

PANEL B: Mean market–adjusted return difference within each *Momentum* category

Holding Period	Worst=LOW: 0.00	0.25	0.50	0.75	Best=HIGH: 1.00
Extreme recommendation *levels* (BUY–SELL) within Momentum Category					
1 month	+0.0002	–0.0068	+0.0014	+0.0023	+0.0054
3 months	+0.0009	–0.0077	+0.0044	+0.0069	+0.0262
6 months	–0.0060	–0.0251 *	+0.0027	+0.0072	+0.0279 **
9 months	–0.0198	–0.0468 ***	+0.0092	+0.0005	+0.0380 **
12 months	–0.0495	–0.0663 ***	+0.0007	+0.0053	+0.0363
Extreme *changes* (INCREASE–DECREASE) within Momentum Category					
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 ***

PANEL C: Mean market–adjusted return difference within each *Contrarian* category

Holding Period	Worst=LOW: 0.00	0.20	0.40	0.60	0.80	Best=HIGH: 1.00
Extreme recommendation *levels* (BUY–SELL) within Contrarian Category						
1 month	+0.0064	+0.0126	+0.0053	+0.0075	+0.0104	+0.0060
3 months	+0.0126	+0.0235	+0.0184	+0.0268	+0.0271	+0.0337
6 months	+0.0046	+0.0351 *	+0.0229	+0.0381 ***	+0.0306 **	+0.0617 ***
9 months	–0.0403	+0.0385	+0.0366	+0.0417 **	+0.0368 **	+0.0718 ***
12 months	–0.0524	+0.0429	+0.0404	+0.0444 **	+0.0248	+0.0719 **
Extreme *changes* (INCREASE–DECREASE) within Contrarian Category						
1 month	+0.0114 **	+0.0067	+0.0081 ***	+0.0112 ***	+0.0106 **	+0.0092 **
3 months	+0.0156 *	+0.0117	+0.0194 ***	+0.0143 **	+0.0228 ***	+0.0117
6 months	+0.0422 ***	+0.0230 **	+0.0174 **	+0.0267 ***	+0.0274 ***	+0.0190
9 months	+0.0418 ***	+0.0264	+0.0296 ***	+0.0282 **	+0.0367 ***	+0.0417 **
12 months	+0.0405 ***	+0.0167	+0.0303 **	+0.0282 *	+0.0418 **	+0.0433

FIGURE 1: Data accumulation periods relative to portfolio formation date

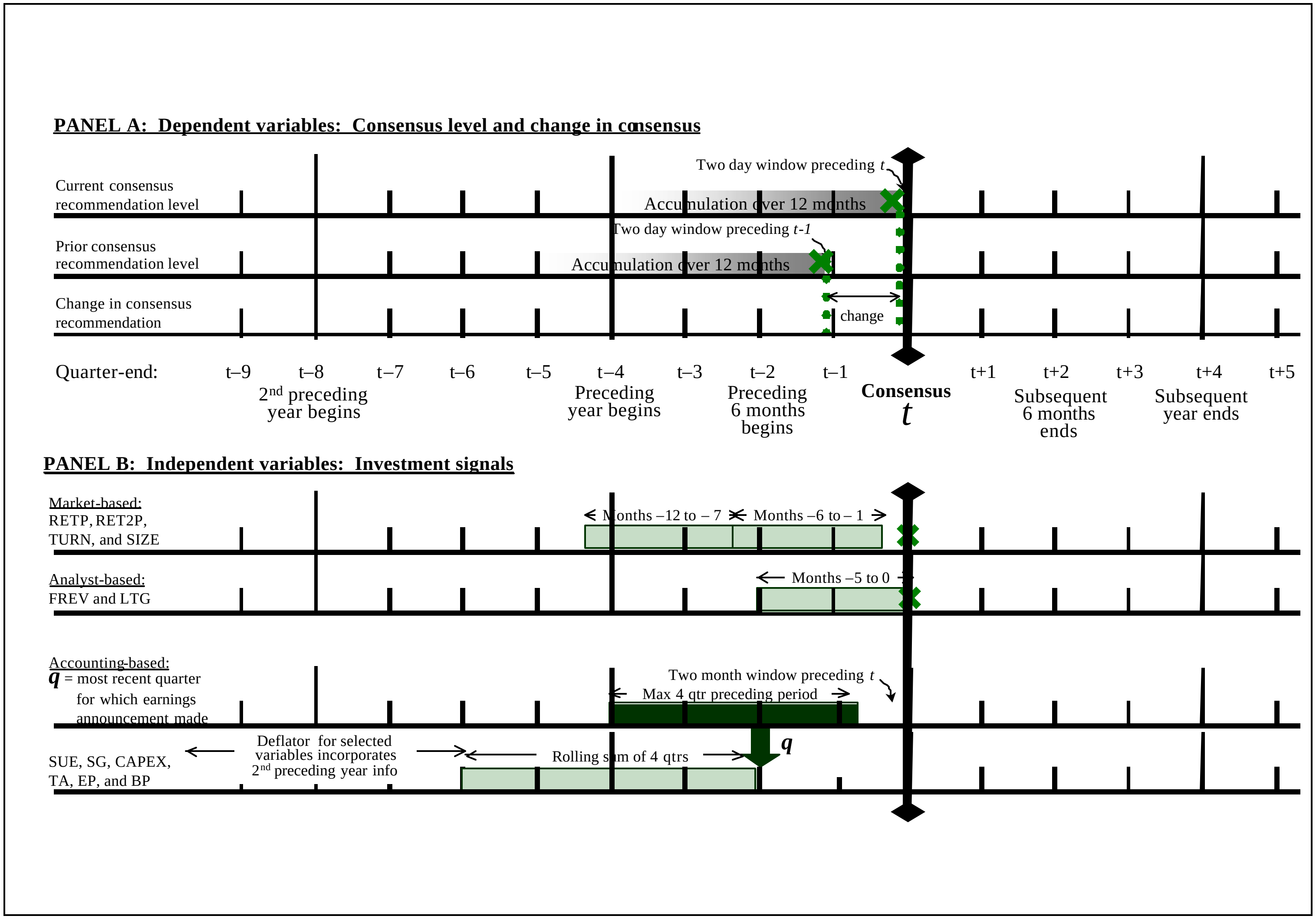

FIGURE 2. Cumulative Excess Returns to Analyst Recommendation Strategies Across Quantitative Categories

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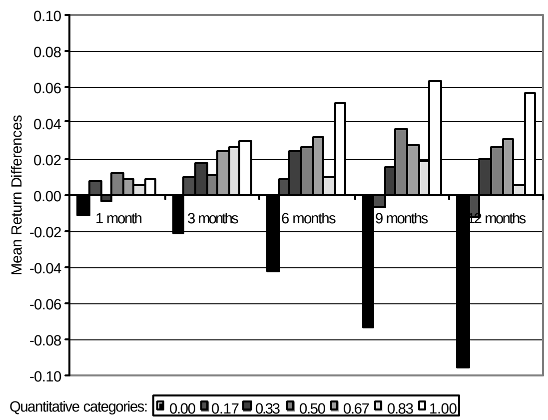
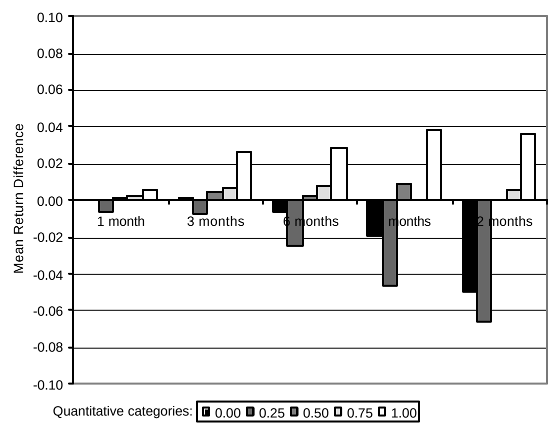
PANEL A: Hedge Returns to Extreme Recommendation *Level* Quintiles (QCON) Across Quantitative Categories

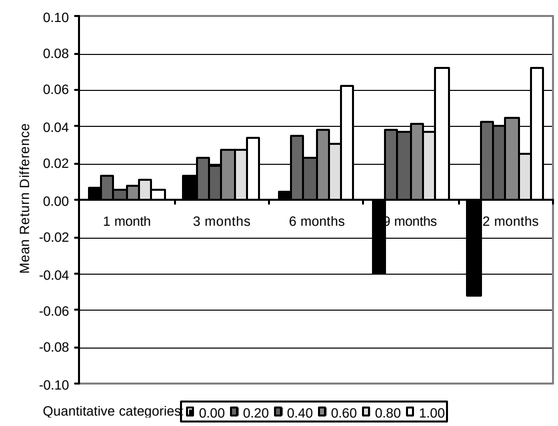
QScore



Momentum

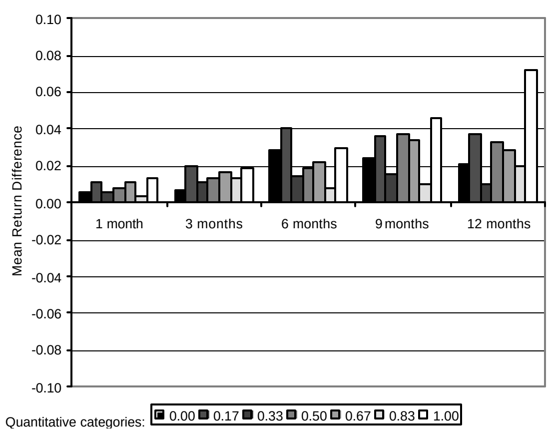


Contrarian

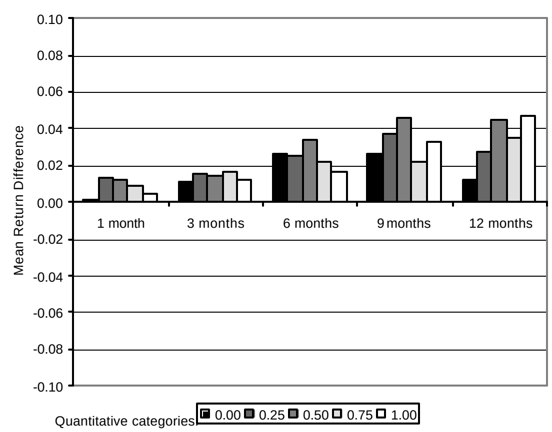


PANEL B: Hedge Returns toExtreme Recommendation *Change* Quintiles (QCHGCON) Across Quantitative Categories

QScore



Momentum



Contrarian