THE JOURNAL OF FINANCE • VOL. LIX, NO. 3 • JUNE 2004

Analyzing the Analysts: When Do Recommendations Add Value?

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ABSTRACT

We show that 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., value stocks and positive momentum stocks). In fact, among stocks with unfavorable quantitative characteristics, higher consensus recommendations are associated with worse subsequent returns. In contrast, we find that the quarterly *change* in consensus recommendations is a robust return predictor that appears to contain information orthogonal to a large range of other predictive variables.

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 more accurately value companies.[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

*Jegadeesh is from Emory University; Kim is from Case Western Reserve University; Krische is from the University of Illinois at Urbana-Champaign; and Lee is from Cornell University. This paper subsumes two earlier manuscripts titled "Stock Characteristics and Analyst Stock Recommendations" and "The Information Content of Analyst Stock Recommendations." We have benefited from the comments of Bill Beaver; Louis Chan; Tom Dyckman; Wayne Ferson; Rick Green (the editor); Paul Irvine; Josef Lakonishok; Jay Ritter; Michael Weisbach; Kent Womack; an anonymous referee; and workshop participants at Case Western Reserve University, Cornell University, Dartmouth College, Emory University, Georgetown University, Rice University, and the Universities of California at Berkeley, Colorado, Illinois at Urbana-Champaign, Pennsylvania, Rochester, and Southern California, as well as the 2002 AFA Annual Meetings, the AIMR Equity Valuation and Research Seminar, and the Prudential Securities Quantitative Research Conference. We would also like to thank Zacks Investment Research for providing the analyst recommendation data and I/B/E/S for providing the analyst earnings forecasts. First Call Corporation also provided us with recommendations data used in an earlier manuscript.

[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).

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, p. 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 this value is the ability of analysts to collect and process firm-specific information useful in identifying undervalued or overvalued stocks. Alternatively, it is possible that analyst recommendations derive their value by tilting toward stocks with particular 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. 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 bias in analyst 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 the 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 demonstrated abilities to forecast cross-sectional differences in 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 capital expenditures constitute a greater proportion of their total assets.

Our results provide a context for understanding the findings from several prior studies. First, we show that stocks favorably recommended by the

[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 predictions may not be the primary goal of analysts.

analysts, on average, outperform stocks unfavorably recommended by them. However, we find that the *level* of analyst recommendation derives its predictive power largely from a tilt toward 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 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 recommendations 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 extend to the type of stocks they choose to recommend. Specifically, our findings suggest that analyst recommendations may be partly driven by incentives that are not entirely aligned with 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 who 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 change*s* in recommendations do provide incremental value. This finding suggests that either: (1) sell-side analysts bring information to the 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) extend the investigation to consensus recommendations, documenting the potential to earn higher returns by buying the most highly recommended stocks and short selling the least favorably recommended stocks. We investigate the extent to which this price drift phenomenon is due to analysts' 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 differences between the value of recommendation levels and changes.

The remainder of the paper is organized as follows. Section I describes the motivation for this study and develops our hypotheses in the context of prior studies. Section II presents our research methodology and sample selection procedures. Sections III and IV evaluate the incremental investment value of recommendations and changes in recommendations. Section V summarizes our findings and discusses some of their implications.

I. 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 value of analyst recommendations in investment decisions, the stock characteristics that we choose to examine have demonstrated abilities to predict returns in the literature. In addition to providing a descriptive profile, we are also interested in assessing

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

how analysts' tilt toward various characteristics helps or hurts 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.

A. Predictive Variables

We consider 12 variables that have demonstrated ability to predict cross-sectional returns. These variables are summarized below. Appendix A presents more detailed information on how each variable is computed.

A.1. Momentum and Trading Volume

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

Prior studies also show that recent earnings momentum predicts cross-sectional differences in returns (e.g., Bernard and Thomas (1989), Chan, Jegadeesh, and 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 overvalued (undervalued) 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

[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.

recommendations to tilt more favorably toward lower-volume stocks than higher-volume stocks.

A.2. Valuation Multiples

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

A.3. Growth Indicators

We include two growth indicators: LTG (the mean analyst forecast of expected long-term growth in earnings) and SG (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 overvalued 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 SG (and low LTG) firms should receive more favorable recommendations.

A.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.

A.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

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

[8] Lakonishok, Shleifer, and Vishny (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.

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 et al. (2001) point out that firms with large sales growth also experience large contemporaneous increases in accounts receivables and inventory, mainly to support the increased levels of sales. In fact, Chan et al. find that the decile of firms with the largest accruals experience sales growth of 22% per year over the prior three-year period compared to seven percent 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 capital expenditure (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 overextend 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 12 variables we use have demonstrated 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.

II. Sample Selection and Research Design

A. 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).

[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.

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.

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

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

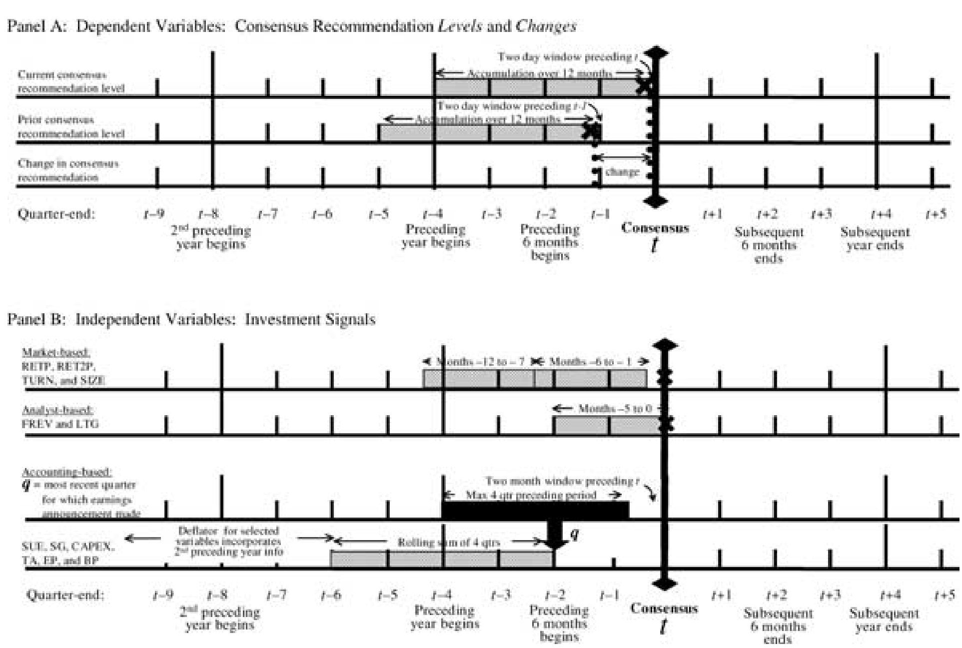

Figure 1. Data accumulation periods relative to portfolio formation date. This figure presents the timeline over which we measure various data items that we use for the computation of consensus recommendations, recommendation changes, and stock characteristics.

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 $t+1$.

Some of the accounting data that we use are announced after the analysts have made their recommendations. However, individual analysts are free to change their recommendations if they believe the newly released data call for a change. Our sample contains both analysts who chose to change their recommendations after the earnings announcements and those who chose to maintain their recommendations. In effect, we treat individual recommendations that enter the computation of the consensus recommendation in the same manner as an investor would when she evaluates stocks at the end of a calendar quarter.

B. Data Description

Our data collection procedure yields an average of 971.4 firm observations per quarter over the 56 quarters. Table I 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 57% (43%) 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 II 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 II 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

[10] Commercial services that report analyst recommendations (e.g., Zacks, First Call, and I/B/E/S) 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 six. 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).

Table I

Description of Sample Firms

This table provides descriptive statistics on the firms included in our sample. Our 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 I/B/E/S information. Panel A reports the mean number of observations per quarter for each individual year and the average level of consensus recommendation. We reverse-score the recommendations from five (strong buy) to one (strong sell). The consensus recommendation is defined as the mean of all individual recommendations two days prior to the end of each calendar quarter. Mean Consensus in the table is the average of the consensus recommendations at the end of each quarter. Panels B and C report the sample distributions across exchanges and size deciles. We include firms with CRSP codes for regional exchanges and the OTC market (0.6% of observations) with the Nasdaq sample. We obtain the exchange listing as of the time of the consensus recommendation. The sample period is from 1985:1 through 1998:4.

Panel A: Sample Distribution across Years

Year	Observations Per Quarter	% of total	Mean Consensus
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
Sample Average	971.43		3.67

Panel B: Sample Distribution across Exchanges

Exchange	Mean Observations Per Quarter	Mean % of Sample Per Quarter
Nasdaq	575.82	57.0
NYSE	263.96	28.7
AMEX	131.64	14.3
Mean Quarterly Sample	971.43	100.0%

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

[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-thirds are “buys” or “strong buys.”

Table I—*Continued*

Panel C: Sample Distribution across NYSE Size Deciles						
	Nasdaq Firms		NYSE/AMEX Firms		Total Sample	
NYSE Size Decile	Mean Obs Per Quarter	% of Sample	Mean Obs Per Quarter	% of Sample	Mean Obs Per Quarter	% of Sample
10 (Largest)	13.79	1.3	73.16	7.8	86.95	9.0
9	26.02	2.4	64.18	6.9	90.20	9.3
8	36.18	3.5	52.79	5.7	88.96	9.1
7	43.46	4.3	44.55	4.8	88.02	9.1
6	48.59	4.8	38.52	4.1	87.11	8.9
5	59.89	6.2	33.38	3.6	93.27	9.8
4	64.93	6.6	29.59	3.3	94.52	9.9
3	78.96	7.8	27.36	3.1	106.32	11.0
2	88.86	8.8	19.13	2.1	107.98	10.9
1 (Smallest)	115.14	11.5	12.96	1.4	128.11	12.8
Mean Quarterly Sample	575.82	57.0	395.61	43.0	971.43	100.0

level. Quintiles are calculated separately for each of the 55 quarters (1.00 = strong increase, 0.50 = hold, 0.00 = strong decrease). Due to the discrete nature of recommendation changes, the quintiles are not of equal size. 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 change*s* in the consensus. A firm that received a relatively high (low) prior recommendation is much more likely to be down (up) graded. For example, 32.2% of the firms in the top quintile in terms of the prior consensus appear in the bottom quintile in terms of change*s* in recommendation. Conversely, 29.0% of the firms in the bottom quintile of prior consensus recommendations appear in the top change*s* quintile.

III. Empirical Results

A. Analyst Recommendations and Future Returns

Table III 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

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

Table II

Description of Analyst Recommendations

This table provides descriptive statistics on the analyst recommendations in our sample. We use all individual recommendations in the Zacks database that have been outstanding for less than one year. We reverse-score the recommendations from five (strong buy) to one (strong sell). We define consensus recommendation as the mean of all individual recommendations two days prior to the end of each calendar quarter. Firms are sorted into quintiles at the beginning of the next quarter based on either the level of the consensus recommendation, or the change in the consensus recommendation over the most recent quarter. Firm-quarter is the unit of observation in Panels A and B. We compute the variables in the table each quarter, and report the summary statistics of the time-series. The sample period is from 1985:1 through 1998:4 for recommendation levels and from 1985:2 through 1998:4 for recommendation changes. Panel A reports summary statistics for each of the level quintiles. The column "Coded as" reports the numerical values assigned to each quintile. The column "Mean Obs" is the average number of stocks in the sample per quarter. Panel B reports the summary statistics for each of the change quintiles. The middle quintile contains all observations with no change in consensus recommendations. Panel C reports the frequency distribution of observations in each change quintile, conditional on its level quintile membership in the prior quarter.

Quintile	Coded as	Mean Obs	Mean	Std Dev	Minimum	Maximum
Panel A: Consensus Recommendation Level Quintiles (Strong BUY = 5, HOLD = 3, Strong SELL = 1)						
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
Panel B: Consensus Recommendation Change Quintiles						
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

Panel C: Percentage of Sample in Recommendation Change Quintile, Conditioned on Prior Consensus Level Quintile

Prior Consensus Quintile	Recommendation Change Quintile: 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%

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 III

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: (1) the consensus recommendation level (CON) and (2) the change in the consensus measured over the prior quarter (CHGCON). Panel A reports the Spearman rank correlation between each analyst recommendation measure and future returns. The column "Continuous Expl. Variable" uses the actual values of recommendation levels and changes, and the column "Categorical Expl. Variable" uses the quintile scores for these variables from Table II. Panel B reports future returns for firms grouped by their consensus recommendation levels (CON), and Panel C reports future returns grouped by the change in the consensus recommendation (CHGCON). We compute the statistics in the table each quarter, and report the means and medians of the time-series. The sample period is from 1985:1 through 1998:4 for recommendation levels and from 1985:2 through 1998:4 for recommendation changes. We indicate two-sided statistical significance at 1%, 5%, and 10% as ***, **, and * respectively. The significance level for the Median is based on the Wilcoxon signed-rank test, and for the Mean is 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 ("CON")	+0.0312**	+0.0276**	+0.0311**	+0.0350**
Consensus Change ("CHGCON")	+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 III (Panel A) confirms the results in prior studies that both CONS and CHGCON are correlated with future returns. The next two panels report the mean and median market-adjusted return in quintile portfolios sorted each quarter by CON, the analyst recommendation level (Panel B), and by CHGCON, the change in analyst recommendation (Panel C). The market-adjusted returns are all negative because we use the value-weighted index as the benchmark, and the large capitalization stocks that have large weights in this index had relatively high returns during our sample period.

The results in Table III (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) 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. 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 III (Panel C) indicate that a trading strategy that buys stocks in the top CHGCON group and sells stocks in the bottom CHGCON group earns 2.7% over the next six months. The relation between CHGCON 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 CHGCON 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 CHGCON 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 starting from a predetermined calendar date. As Barber et al. (2001a) point 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.

B. *Other Investment Strategies*

Table IV reports the Spearman rank correlation between future returns and other investment strategies. Over our sample period, most of these variables

[13] As we report in more detail later, we do not observe a significant drift after six months.

Table IV

Quantitative Investment Signals and Future Returns

This table presents the Spearman rank correlation between future returns (RETF) and various quantitative investment signals. We define RETF as the market-adjusted return in the six months following the month of the recommendation. The 12 quantitative investment signals are described in detail in Appendix A. For variables that are positively (negatively) correlated with future returns, the binary variable assumes a value of one if the explanatory variable is higher (lower) than the median for that quarter, and zero otherwise. The net portfolio return is the mean difference in future returns between the portfolio of firms with the binary variable equal to one, and the portfolio of firms with the binary variable equal to zero. Our estimates are formed once each quarter for the 56 quarters from 1985:1 to 1998:4. We aggregate these quarterly estimates and report their time-series averages. The column "% Positive Returns" presents the percentage of the 56 quarters in which the net portfolio return was greater than 0%. We indicate two-sided statistical significance at 1%, 5%, and 10% as ***, **, and * respectively, based on t-statistics calculated with autocorrelation consistent standard errors (as described in Appendix B).

Explanatory Variable	Continuous Explanatory Variable Correlation	Binary Explanatory Variable: Normative Definition	Correlation	Mean Net Portfolio Return	% Positive Returns
RETP	+0.080***	1 if greater than median, 0 otherwise	+0.064***	+0.032***	76.79
RET2P	+0.043***	1 if greater than median, 0 otherwise	+0.039***	+0.013*	62.50
TURN	−0.034**	1 if less than median, 0 otherwise	+0.033**	+0.002	62.50
SIZE	+0.088***	1 if less than median, 0 otherwise	−0.077***	−0.016	35.71
FREV	+0.099***	1 if greater than median, 0 otherwise	+0.091***	+0.042***	83.93
LTG	−0.006	1 if less than median, 0 otherwise	+0.008	−0.000	53.57
SUE	+0.053***	1 if greater than median, 0 otherwise	+0.040***	+0.018**	67.86
SG	−0.025*	1 if less than median, 0 otherwise	+0.025*	+0.004	57.14
TA	−0.081***	1 if less than median, 0 otherwise	+0.063***	+0.029***	85.71
CAPEX	−0.021*	1 if less than median, 0 otherwise	+0.023**	+0.015***	69.64
BP	−0.016	1 if greater than median, 0 otherwise	−0.010	−0.000	50.00
EP	+0.038**	1 if greater than median, 0 otherwise	+0.029**	+0.004	55.36

are correlated with future returns in the directions reported in prior studies. The two exceptions are SIZE and BP. In the 1985 through 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 earnings momentum (FREV and SUE), and low trading volume (TURN) earn higher returns over the next six months. Similarly, low SG, low TA, and low 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 assign a value of one if it is higher (lower) than its median value in a given quarter, and zero 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 the essence of how these signals work together in quantitative investment strategies. We chose this simple measure rather than conduct a search for a more efficient return predictor because it is not our goal to create an optimal measure to predict future returns.

We also separately compute a 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 "Correlation," Table IV reports 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 one) and the portfolio of bottom firms (with binary variable equal to zero). The final column in this table reports the proportion of sample quarters (out of a total of 56) in which the net portfolio return

[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 one if SIZE is less than the median, and zero otherwise.

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 V 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: (1) Momentum (the sum of the four momentum signals: RETP, RET2P, FREV, and SUE), (2) Contrarian (the sum of the remaining signals, excluding firm size), and (3) QScore (the sum of all 12 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 an average of at least about 100 stocks per quarter. 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.

C. 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 analyst stock recommendations. In this section, we examine the relation between analyst recommendations and various investment signals.

Table VI 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 vary monotonically across recommendation quintiles. These variables are indicated by a "+" or "–" symbol under the heading "Actual Direction." 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 exhibits a strong preference for positive momentum stocks—the Spearman rank

Table V

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. We use three different summary variables: 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). Appendix A describes the signals. We combine extreme categories of the summary variables, such that the extreme groups have an average of at least about 100 stocks per quarter. Panel A reports the Spearman rank correlation between each sum measure and future returns. Panels B, C, and D report future returns for firms grouped by QScore categories, Momentum categories, and Contrarian categories, respectively. We compute the variables in the table each quarter, and report the means and medians of the time-series. The sample period is from 1985:1 through 1998:4 for recommendation levels and from 1985:2 through 1998:4 for recommendation changes. We indicate two-sided statistical significance at 1%, 5%, and 10% as ***, **, and * respectively. The significance level for the Median is based on the Wilcoxon signed-rank test, and that for the Mean is 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	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 VI

Descriptive Statistics by Consensus Recommendation Quintile

This table examines the relation between the level of the consensus recommendation and 12 investment signals. The signals are described in detail in Appendix A. Our unit of observation is firm-quarter. To construct Panel A, we sort all firms by their consensus recommendation levels and group them into quintiles each quarter. Table values are the time series means of the investment signal for each recommendation quintile. "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. When the absolute value of correlation is less than 10%, the table indicates the actual direction as "?." Panel B presents this analysis for changes in consensus recommendations. The sample period is from 1985:1 through 1998:4 for recommendation levels and from 1985:2 through 1998:4 for recommendation changes.

Panel A: Consensus Recommendation Level

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

Table VI—*Continued*

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

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 direction 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 VII 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. In each quarter, 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 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,

[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 with Bradshaw, because even in our sample, analysts exhibit a strong preference for high LTG firms (Spearman rank correlation of 27.2%).

respectively. With a few exceptions, Table VII confirms the univariate results reported in Table VI. 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

Table VII

Regression of Recommendations on Explanatory Variables

This table reports the result when analyst recommendations levels and changes are regressed on various explanatory variables. Panel A (Panel 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, we standardize the explanatory variables by subtracting their means and dividing by their standard deviations each quarter. We obtain the regression estimates each quarter, and report the time-series averages of the estimates. The column "Normative Direction" indicates the sign of the variable's correlation with future returns from prior studies. The column "Actual Direction" indicates the sign of the relation when the rank correlation is 10% or higher. When the absolute value of correlation is less than 10%, the table indicates the actual direction as "?." Mean R^2 and Mean F-statistic are the averages of the respective statistics from the quarterly cross-sectional regressions. The sample period is from 1985:1 through 1998:4 for recommendation level*s* and from 1985:2 through 1998:4 for recommendation changes. We indicate two-sided statistical significance at 1%, 5%, and 10% as ***, **, and * respectively, based on t-statistics calculated with autocorrelation consistent standard errors (as described in Appendix B).

Panel A: Consensus Recommendation Level ("CON")

Variable	Normative Direction	Actual Direction	Regression Coefficient	t-statistic
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**
Mean R^2	25.70%			
Mean F-statistic	27.53			

Table VII—*Continued*

Panel B: Consensus Recommendation Change ("CHGCON")				
Variable	Normative Direction	Actual Direction	Regression Coefficient	t-statistic
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
Mean R^2	14.88%			
Mean F-statistic	12.43			

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. (2001)). 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 relation 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 we observe 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.

IV. 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.

A. 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 VIII 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 variable 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 it 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

Table VIII

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 V. The variables $QFIT_{CON}$ and $QFIT_{CHGCON}$ are fitted values of QCON and QCHGCON from Panels A and B of Table VII, respectively. We obtain the regression estimates each quarter, and report the time-series averages of the estimates. The sample period is from 1985:1 through 1998:4 for recommendation levels and from 1985:2 through 1998:4 for recommendation changes. We indicate two-sided statistical significance at 1%, 5%, and 10% as ***, **, and * respectively, based on t-statistics calculated with autocorrelation consistent standard errors (as described in Appendix B).

Panel A: Consensus Recommendation Level Quintiles (QCON)

	Model A1		Model A2		Model A3		Model A4		Model A5		Model A6	
	Analysts Alone		Analysts & Both Summary Variables		Analysts & Momentum Summary Variable		Analysts & Contrarian Summary Variable		Analysts & Binary Investment Signals		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***		
$QFIT_{CON}$											+0.0300	2.32**

Table VIII—*Continued*

Panel B: Consensus Recommendation Change Quintiles (QCHGCON)												
	Model B1		Model B2		Model B3		Model B4		Model B5		Model B6	
	Analysts Alone		Analysts & Both Summary Variables		Analysts & Momentum Summary Variable		Analysts & Contrarian Summary Variable		Analysts & Binary Investment Signals		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***		
$QFIT_{CHGCON}$											+0.0159	2.20**

six-month profits to a strategy that buys the stocks with a signal of one and sells the stocks with a signal of zero 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 is 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 *t*-statistics on these variables appear large, but are consistent with prior studies in which they appear (e.g., Sloan (1996), Collins and Hribar (2000), Chan et al. (2001), Gleason and Lee (2003), Beneish et al. (2001), and Stickel (1991)).[16]

The QCON coefficient, however, is not statistically significant in this regression. This coefficient is positive in only 32 out of the 56 quarters. As a final test, we fit a regression where the independent variable that we use in addition to QCON is its fitted value ($\mathrm{QFIT}_{\mathrm{CON}}$) from the regression in Table VII Panel A (Model A6). Interestingly, QCON is not statistically significant in this regression, but $\mathrm{QFIT}_{\mathrm{CON}}$ is significant. Collectively, the evidence from these regressions suggests that while QCON is weakly correlated with returns, its contribution is largely due to its tilt toward other firm characteristics that are related to future returns.[17]

Our conclusions about the incremental value of the level of analyst recommendations differ from those in Barber et al. (2001a). Barber et al. 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, a momentum factor, and a market factor. The main reason why our conclusions are different from those in Barber et al. is that we control for the effect of earnings momentum in addition to the other factors in the four-factor model. In fact, earnings momentum plays an important role in explaining the value of the level of analyst recommendations.

In addition, our controls are based on stock characteristics, while the benchmark four-factor model in Barber et al. (2001a) accounts for the effect of momentum and other factors based on factor sensitivities. As Daniel and Titman (1997) find, characteristic-based controls are more reliable than factor sensitivity-based controls. In fact, it is doubtful that the sensitivity to the momentum factor

[16] We find that the *t*-statistic on the TA coefficient is larger than the *t*-statistic that Sloan (1996) reports for a trading strategy based on TA. We find a stronger TA effect mainly because we include Nasdaq firms in our sample, and also because the TA strategy profit is larger in the period after the sample period in Sloan. During the period of overlap (1985–1991), and including only NYSE/AMEX firms, we find very similar results to Sloan. The *t*-statistic on the FREV variable is also large, but earlier papers by Stickel (1991) and Beneish et al. (2001) report *t*-statistics of a similar magnitude.

[17] 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.

in the four-factor model even fully accounts for the price momentum effect in our context. For instance, we find a strong monotonic relation between price momentum and analyst recommendations in Table VI. However, the Barber et al. results indicate that the momentum factor sensitivity does not vary monotonically across recommendation quintiles. In particular, their results indicate that the middle portfolio has the highest sensitivity to the momentum factor, while we find that the most favorably recommended portfolio has the largest price momentum. 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 characteristic-based benchmark that includes controls for earnings momentum.

Table VIII, Panel B reports the results for regressions with QCHGCON. Model B1 shows that QCHGCON is able to predict future returns. The estimated coefficient (2.25%) can be interpreted as the hedge return between the extreme CHGCON categories over the next six months. Next we consider multiple regressions with CHGCON and the other independent variables that we earlier used with QCON. In the last regression specification (Model B6), we include the fitted value ($QFIT_{CHGCON}$) for QCHGCON from the regression in Table VII 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. Finally, Model B6 shows that QCHGCON is significant with the inclusion of $QFIT_{CHGCON}$. These results consistently indicate that QCHGCON is incrementally useful in predicting returns.[18]

B. 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 have 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 IX reports results of a two-way analysis, where we independently sort firms by their quantitative summary score (QScore), as well as by their analyst recommendation. Panel A of this table reports results for the level of the consensus recommendation (CON). Panel B reports results for the change in the consensus recommendation (CHGCON). The intersection of analyst recommendation quintile ranks and characteristic septile ranks yields 35 portfolios for each two-way sort. We equally weight all stocks in each portfolio.

[18] 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.

Table IX

Future Returns by Quantitative Scores and Analyst Recommendations

This table reports the market-adjusted return in the six months following the recommendation. We group firm group by their quantitative scores (QScore) and consensus recommendations. The QScores are the sum of 12 signals (RETP, RET2P, FREV, SUE, EP, BP, TURN, LTG, SG, TA, CAPEX, and SIZE). Panels A and B report results for the recommendation level quintiles (QCON) and change quintiles (QCHGCON), respectively. We form the portfolios at quarterly intervals, and report the time-series mean returns. The sample period is from 1985:1 through 1998:4 for recommendation levels and from 1985:2 through 1998:4 for recommendation changes. We indicate two-sided statistical significance at 1%, 5%, and 10% as ***, **, and * 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* Category

		Consensus Recommendation Level Quintile											
		Worst = SELL: 0.00		0.25		0.50		0.75		1.00: Best = BUY			
QScore Category		Obs	Mean	Obs	Mean	Obs	Mean	Obs	Mean	Obs	Mean	BUY-SELL	t-statistic
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-statistic			+3.04***		+1.89*		+1.53		+4.64***		+8.82***		
Overall analysts' level recommendations = Buy−Sell (see also Table III, Panel B)												+0.0216	+1.86*
Overall quantitative strategy = High−Low (see also Table V, 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 IX—*Continued*

Panel B: Market-adjusted Returns by Recommendation *Change* Quintile and *QScore* Category

		Consensus Recommendation Change Quintile											
		Worst = Decr: 0.00		0.25		0.50		0.75		1.00: Best = Incr			
QScore Category		Obs	Mean	Obs	Mean	Obs	Mean	Obs	Mean	Obs	Mean	Incr-Decr	t-statistic
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-statistic			+3.84***		+1.61		+5.65***		+3.62***		+4.59***		
Overall analysts' change recommendations = Incr − Decr (see also Table III, Panel C)												+0.0268	+5.81***
Overall quantitative strategy = High − Low (see also Table V, 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 A reports six month market-adjusted returns of firms sorted by CON 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 analyst recommendation. High QScore firms earn higher subsequent returns in all analyst recommendation categories. The QScore variable 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 (CON) have some limited predictive power after controlling for QScore, but this power is conditional on the QScore category. Specifically, CON is only useful among high QScore firms. In the highest QScore category, top CON quintile firms earn 5.04% more than bottom CON quintile firms over the next six months. However, for firms with a low QScore, the return to a CON strategy is −4.27%. This result suggests that among low QScore stocks, firms more highly recommended by the analysts actually do worse than firms with low recommendations.

Another result that emerges from this table is that when analyst recommendations and the QScore disagree, the QScore 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. Specifically, both in Panel A and Panel B, firms in the lower-left corner (high QScore firms with the worst recommendation levels or changes) earn higher average returns than firms in the upper-right corner (low QScore firms with the best recommendation levels or changes). For instance, the return difference between these "DISAGREE" portfolios is −9.51% in Panel A, which is statistically significant at the 1% level. Evidently, when the two signals are in conflict, QScore results in more reliable returns predictions.

Finally, we find the highest predictive power for returns when analyst recommendations and the QScores agree. 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 both panels, the Best-and-High group earns higher returns than the Worst-and-Low group. The return differences are 9.28% in Panel A and 10.11% in Panel B. Therefore, the combined strategy generates higher returns than those earned by independently considering each signal.

Table X 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, or Contrarian) and by their consensus recommendation (either CON or CHGCON). Panel A reports the mean difference in market-adjusted returns between the extreme CON groupings

(BUY-SELL) and between the extreme CHGCON groupings (INCREASE-DECREASE) within each of the QScore categories over 56 quarters for CON and 55 quarters for CHGCON. Panels B and C repeat the analyses for Momentum and Contrarian categories, respectively. We report the cumulative excess return for one, three, six, nine, and 12 month holding periods for each

Table X

Cumulative Returns Difference over Various Holding Periods

This table reports the return differences over various holding periods following portfolio formation. We group firms by their quantitative measure (QScore, Momentum, Contrarian) and consensus recommendations. Panel A reports the mean difference in 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. We compute the return differences quarterly, and report the time-series means. The sample period is from 1985:1 through 1998:4 for recommendation levels and from 1985:2 through 1998:4 for recommendation changes. We indicate two-sided statistical significance at 1%, 5%, and 10% as ***, **, and * respectively, based on t-statistics calculated with autocorrelation consistent standard errors (as described in Appendix B).

Panel A: Return Difference within QScore Categories

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 Categories							
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 Categories							
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: Return Difference within *Momentum* Categories

Holding Period	Worst = LOW: 0.00	0.25	0.50	0.75	Best = HIGH: 1.00
Extreme Recommendation Levels (BUY – SELL) within Momentum Categories					
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 Categories					
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***

Table X—*Continued*

Panel C: Return Difference within *Contrarian* Categories						
Holding	Worst = LOW:					Best = HIGH:
Period	0.00	0.20	0.40	0.60	0.80	1.00
Extreme Recommendation Levels (BUY – SELL) within Contrarian Categories						
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 Categories						
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

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 analysts' predictive power derives from their tendency to select positive momentum stocks.

Third, like Barber et al. (2001a), we find that the dissipation of mean profits is quite rapid. Direct comparison to Barber et al. is difficult because, unlike Barber et al., our trading strategy does not take a position immediately after each individual analyst recommendation. Rather, we form portfolios at the end of each quarter. Thus, our strategy excludes returns earned between the announcement date and the end of the quarter. Nevertheless, Table X shows that most of the cumulative excess returns are earned in the first three to six months after portfolio formation.

Finally, Table X shows that the main reason the CON 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 CON 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 CON and CHGCON 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 CON 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 (CON) 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 CHGCON. In all subportfolios and over all holding periods, this strategy results in positive excess returns, although they are not statistically significant in several instances. In other words, 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 VIII–X 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.

V. 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

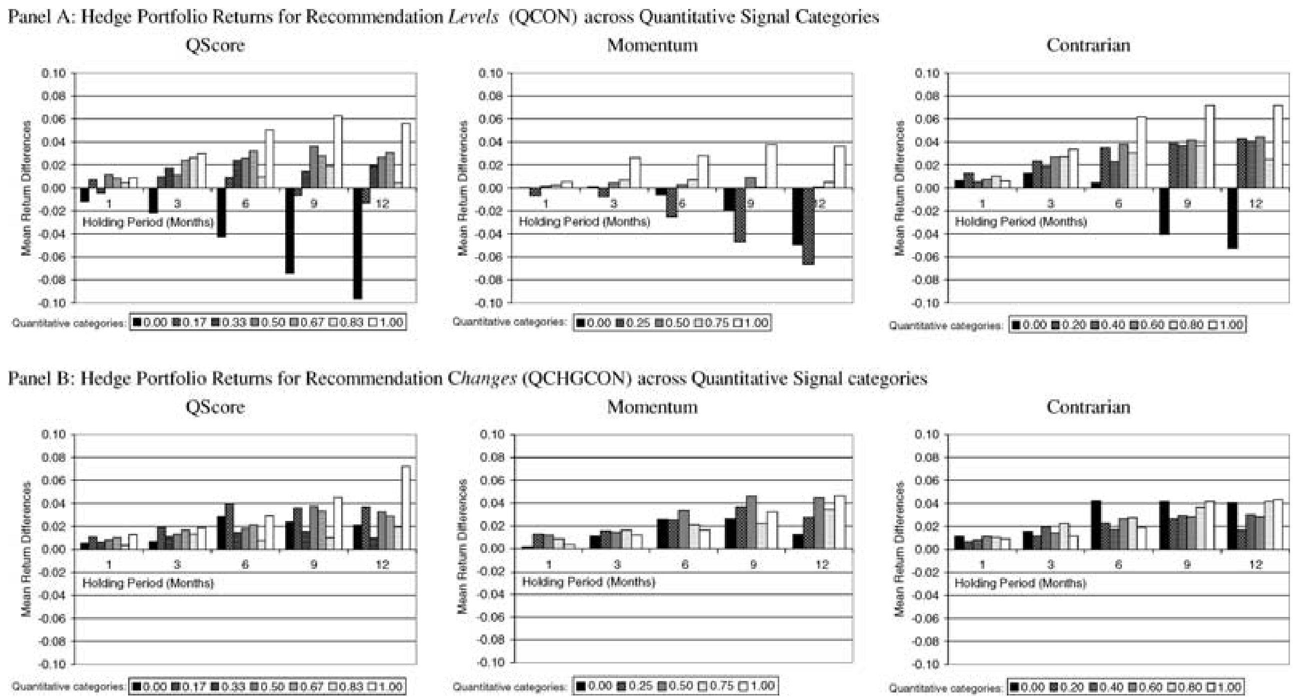

Figure 2. Cumulative excess returns to analyst recommendation strategies across quantitative signal categories. This figure presents the difference between the returns of the extreme quintile portfolios ("Hedge portfolio returns") formed based on recommendation levels (Panel A), and changes in recommendations (Panel B), within each quantitative signal category, for holding periods ranging from 1 to 12 months. The x-axis presents the holding periods. We use three different quantitative signals: 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). Appendix A describes the signals. For each quantitative signal, we partition the sample into "Quantitative categories" using the cutoffs described in Table IV.

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 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 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 recommend firms with lower trading volume, higher EP ratios, lower LTG and SG measures, more negative (income decreasing) accruals, and lower capital expenditures.[19]

From an investment perspective, our results suggest analyst recommendations play a dual role in the price formation process. On the one hand, analysts seem overenamored 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 (three 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 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 (3–12 month ahead) returns, sell-side analysts should pay more attention to the results of documented relations between stock characteristics and future returns. On the other hand, quantitative investors could also benefit by augmenting their stock selection process with the consensus recommendation of sell-side analysts.

Appendix A: Investment Signals

This appendix provides a detailed description of the 12 investment signals used in the study. All these explanatory variables are Winsorized at the $2^1/_2$ and $97^1/_2$ percentiles within each quarter. [*Source*] 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

[19] 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 (2003)).

consensus recommendation levels and changes are collected at the end of quarter t, which has month-end m. We denote the most recent quarter for which an earnings announcement was made as q. We require the announcement to be made at least two months prior to the end of quarter t, and that $q \geq t-4$.

Variable	**Description**	**Calculation Detail [*Source*]**
1. RETP	Cumulative market-adjusted return for the preceding six months (months −6 through −1)	$\{[\Pi_{i=m-6}^{m-1}(1+\text{monthly return}_i)]-1\}$ $-\{[\Pi_{i=m-6}^{m-1}(1+\text{value}-\text{weighted market monthly return}_i)]-1\}$, where m = month-end of quarter t [*CRSP*]
2. RET2P	Cumulative market-adjusted return for the second preceding six months (months −12 through −7)	$\{[\Pi_{i=m-12}^{m-7}(1+\text{monthly return}_i)]-1\}$ $-\{[\Pi_{i=m-12}^{m-7}(1+\text{value}-\text{weighted market monthly return}_i)]-1\}$, where m = month-end of quarter t [*CRSP*]
3. TURN	Average daily volume turnover	Percentile rank $\left[\frac{\sum_{i=1}^{n}\text{Daily volume/Shares outstanding}}{n}\right]$, by exchange, where n = number of days available for six months preceding the end of quarter t (months $m-6$ through $m-1$) [*CRSP*]
4. SIZE	Market cap (natural log)	*LN* ($P_q \times$ Shares Outstanding$_q$) = LN (price at the end of the quarter q [D14], multiplied by common shares outstanding at the end of quarter q [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 the end of quarter t [*IBES*]
7. SUE	Standardized unexpected earnings	$\frac{(EPS_q - EPS_{q-4})}{\sigma_q}$, 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] σ_q = standard deviation of unexpected earnings over eight preceding quarters (quarters $q-7$ through q)

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 $q \geq t-4$ 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 $q \geq t-4$ $\Delta X_q = X_q - X_{q-4}$, e.g., $\Delta\text{Current Assets}_{t-1} = \text{Current Assets}_{t-1} - \text{Current Assets}_{t-5}$
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 $q \geq t-4$ $CAPEX_q$ = 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	$\frac{\text{Book value of common equity}_q}{\text{Mktcap}_q}$, where q = most recent quarter for which an earnings announcement was made a minimum two months prior to the end of quarter t, with $q \geq t-4$ *Book value of common equity*$_q$ = book value of total common equity at the end of quarter q [D59] $Mktcap_q = P_q \times Shares\ Outstanding_q$ = price at the end of the quarter q [D14], multiplied by common shares outstanding at the end of quarter q [D61]
12. EP	Earnings to price	$\frac{\sum_{i=0}^{3} EPS_{q-i}}{P_q}$, 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 = earnings per share before extraordinary items for quarter q [D19] P_q = price at the end of the quarter q [D14] Thus, $\frac{\sum_{i=0}^{3} EPS_{q-i}}{Pq}$ = rolling sum of EPS for preceding four quarters, deflated by price

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

We compute a trailing-12-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 3^{rd} 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:

$$\bar{x} = \sum_{t=1}^{T} x_t, \tag{B1}$$

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:

$$\mathrm{Var}(\bar{x}) = \frac{1}{T^2}\left(T \times \mathrm{Var}(x_t) + 2\sum_{k=1}^{K}(T-k)\mathrm{SCOV}_k(x_t)\right), \tag{B2}$$

where, Var is the variance, and $SCOV_k$ is the k^{th}-order serial covariance, and K is the number of nonzero 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 III: 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 IV and V: We follow the same procedure as for Table III.

Table VII: 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 VIII: 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 IX: Same as Table III.

Table X: 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.

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