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Analysts, Industries, and Price Momentum

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Comments Welcome

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Abstract

This paper examines the competition among sell-side analysts, who are predominately industry specialists, to provide investment value through their recommendations within their followed industries. An industry-based strategy of buying stocks net upgraded in each industry and shorting stocks net downgraded in each industry earns 1.4% per month, or about 18% annualized. These returns have a Sharpe ratio five times larger than typical price momentum strategies. When these post recommendation one-month returns are examined industry by industry, they are remarkably consistent. They are positive for 53 of the 59 industries over our 1996-2001 time period. Competition among analysts reduces the opportunity to profit from recommendation changes: portfolios limited to stocks followed by the largest number of analysts earn substantially lower returns.

We also document the strong link between price momentum and analyst recommendations. Stocks recently upgraded or downgraded by analysts are more likely to be included in future Jegadeesh and Titman-type (1993) momentum portfolios. And, analysts are more likely to make recommendation changes for stocks recently included in these portfolios. Returns from recently recommended stocks account for 37% of the returns of the typical price momentum strategy.

JEL Classification: G14, G24

Keywords: Sell-Side Research; Value of Brokerage Recommendations; Market Efficiency; Price Momentum; Sector Rotation.

With few exceptions, the Wall Street analysts that write reports, estimate earnings, help underwrite new issues, and issue buy and sell recommendations are considered industry specialists. Brokerage research departments are predominantly organized by industry, and analysts are regularly compared and evaluated relative to their competitors in the same industry. The *Institutional Investor* All-Star rankings published each October are a prime example of the reputational rewards that accrue to the most highly regarded analysts in each industry. Krigman, Shaw, and Womack (2001) show that *Institutional Investor* All-Star reputations of industry-specific analysts are instrumental in garnering highly profitable investment-banking business for the star analyst's firm.

Since analysts typically follow a small number of stocks (usually from 5 to 30) in one industry and are themselves ranked within industries, it would be reasonable to assume that their stock picking ability, if any exists, should most likely be in ranking the stocks within their industry as winners and losers. Surprisingly, previous research on analysts' recommendations has done little to examine investment strategies based on the presumption of competition among analysts to pick relative winners and losers within their industry.[1] Can and do analysts identify future winning and losing stocks within their industry specializations? We will start by addressing that question.

Among the documented challenges to efficient market theory, one of the most difficult to explain is the abnormal return from price momentum strategies. Jegadeesh and Titman (2001a, 2001b) note that abnormal returns to price momentum strategies, first

[1] Stickel (1995), Womack (1996), and Barber, Lehavy, McNichols, and Trueman (2001) document that returns for stocks upgraded continue to increase (after risk and market adjustments) and stocks downgraded continue to decrease for a month or more after an analyst recommendation change. Barber, Lehavy, McNichols, and Trueman (2001, 2002) find that excess returns from portfolios based on highest and lowest absolute consensus levels may not exceed transactions costs. These analyses do not examine industry-diversified portfolios or analysts' abilities to distinguish winners from losers within their industry specializations.

documented by Jegadeesh and Titman (1993), persist despite their popularity.[2] Hong, Lim, and Stein (2000) link the phenomenon of price momentum with analyst following, which gives support to the hypothesis of Hong and Stein (1999) that momentum is a symptom of investors' collective under-reaction to individual pieces of private information. They use analyst following as a proxy for intensity of information dissemination, and, after controlling for size, find that price momentum is greater where analyst coverage is lower.

Do analysts upgrade past winners and downgrade past losers, possibly to take advantage of the well-documented price momentum? Does post-recommendation price drift contribute to the abnormal returns offered by price momentum strategies? While we do not exhaust all or possibly the most optimal strategies for maximizing future returns, we find that a simple self-financing strategy of buying net upgraded firms and selling net downgraded firms within each industry each calendar month yields a substantial 1.4% in the next calendar month, or about 18% annualized. These returns are well diversified by industry and quite stable over the January 1996 to June 2001 timeframe of this study.

Moskowitz and Grinblatt (1999) and Grundy and Martin (2001) examine whether price momentum is primarily an industry-driven phenomenon. We form both Jegadeesh and Titman momentum portfolios and industry momentum portfolios. Returns from both types of momentum portfolios load heavily on a recommendation-portfolio return factor. The recommendation-based portfolio returns, while loading on the momentum-return factor, are substantially less volatile than those from the momentum portfolios. Interestingly, the recommendation-based portfolios avoid the negative January effect documented by others for Jegadeesh and Titman momentum portfolios.[3]

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[2] Grinblatt, Titman, and Wermers (1995) and Chen, Jegadeesh, and Wermers (2000) show that mutual fund managers buy past winners and sell past losers consistent with the use of momentum strategies. Badrinath and Wahal (2002) show that institutional investors act like momentum traders when they initiate positions.

[3] For example, see Jegadeesh and Titman (1993, 2001b) and Grundy and Martin (2001).

Using chi-square tests, we document that stocks recently recommended by analysts are more likely to be included in momentum portfolios but that analysts are also more likely to recommend momentum stocks. Returns from recently recommended stocks account for 37% of the returns of the typical (six-month) Jegadeesh and Titman momentum strategy.

Jegadeesh, Kim, Krische, and Lee (2002), using quarterly data for 1985 through 1998, find that 1) *quarterly* changes in the consensus level of analyst recommendations offer predictive power for future returns and implementable trading strategies, and 2) analysts are more likely to issue favorable recommendations for positive momentum, high growth, high volume, relatively expensive (i.e., "glamour") stocks. While our paper complements the work of Jegadeesh et al, it differs in some important ways. First, our industry-diversified portfolio strategies measure analysts' intra-industry stock-picking ability, consistent with how they are regularly compared and evaluated relative to their competitors. Interestingly, we find that analysts' ability to pick winners and losers within the industry they specialize is remarkably consistent: mean monthly returns from self-financing portfolios of net upgraded less net downgraded stocks are positive for 53 of the 59 industries over our 6-year period.

Second, while Jegadeesh et al implement strategies based on changes in consensus levels from one quarter to the next, we use a finer one-month filter for recommendation changes. In fact, we conclude that most of the value of recommendations is derived within the first month or two following recommendation changes.

Third, we examine recommendations during a more recent period (1996-2001), one that experienced both boom and bust and that critics have argued was fraught with increased analyst conflicts of interest and positive recommendation biases.[4] We document significant analysts' intra-industry stock-picking ability despite these issues. There are limits however. For the most widely-covered stocks (with analyst following of 15 analysts or more), we show recommendation changes yield little value for the monthly-rebalancing strategies we examine. This finding is consistent with the advent of the day-trader in the late 1990s and Busse and Green (2002), who show that traders respond to televised analysts' recommendations. For less widely-covered stocks, however, slow incorporation of analyst information persists for a month or more following recommendation changes.

Using recommendation information from 1989-1991, Womack (1996) showed that post-recommendation drift was greater for stocks with smaller market capitalizations. Indeed we find returns from recommendation-based portfolios decrease with market capitalization. We show that it is wide analyst coverage, not market capitalization, which eliminates the value from trading on recommendation changes. Interestingly, when portfolios are restricted to upgraded and downgraded stocks of companies with the greatest market capitalization (CRSP decile 10), returns remain positive and significant.

The rest of the paper proceeds as follows. Section I describes the dataset and methodology used in the paper. Sections II and III discuss the empirical results for recommendation and momentum portfolios respectively. Section IV further examines the link between analyst recommendations and momentum. Section V discusses the implications of our findings and concludes.

[4] See Boni and Womack (2002a, 2002b) for surveys of the analyst conflicts of interest literature. Barber et al (2001, 2002) document the increase in ratio of buy to sell recommendations from 1986 to 2000.

I. Data and Methodology

A. The Dataset

We construct our dataset using IBES data on analyst recommendations and consensus levels, CRSP monthly stock returns and market capitalizations, and industry codes as defined by the Global Industry Classification Standard (GICS) by Standard & Poor's (S&P) and Morgan Stanley Capital International (MSCI). We include all NYSE, AMEX, and Nasdaq companies that have CRSP monthly returns and can be matched with a GICS industry code using Compustat. The timeframe for our study is constrained by the analyst recommendation data, which cover the period January 1996 through June 2001, and the CRSP data, through the end of calendar year 2001.

IBES provides two recommendations databases. The Summary History-Recommendation file compiles a monthly snapshot of each company followed by sell-side analysts whose brokerage firm provides data to IBES. This database tracks at mid-calendar month (similar to the Summary History-EPS file) the number of analysts following the stock, the average consensus rating level on a 1 to 5 scale (where 1 is a "strong buy" and 5 is a "sell") and its standard deviation for the stock, and the number of analysts upgrading and downgrading their opinion level in the month. The Detail History-Recommendation file provides a database entry for each recommendation change made by each analyst. Important variables include the date of the change, the analyst and the brokerage firm's name, and to what level the change was made. Of the 12,028 companies in our dataset, 4,262 are "neglected" firms, i.e., they have no recommendation or consensus level data per IBES.

In the 1996 to 2001 timeframe, there are 84,100 recommendation changes from one rating level to another. In addition to changes, where both an earlier level and the new current level are identified, we also include 67,567 "first recommendations", which are recommendations where we obtain the new current level, but do not explicitly know the previous rating level, either because it did not exist (if an analyst initiates coverage) or because the company could not be matched to an earlier rating in the database.[5] Although common in the communications of analysts to their clients, reiterations of prior ratings levels are not part of the IBES databases.

Table 1 shows the brokerage firm characteristics of the 151,667 recommendation changes in our sample. There were 7,766 companies followed during at least one month of the timeframe that we examine. As shown in Table 1, the largest 24 brokerage firms account for almost half the recommendations.

[Table 1 about here.]

The S&P/MSCI GICS classifies companies at four levels. Each company is assigned to one of 10 sectors, 23 industry groups, 59 industries, and 122 sub-industries.[6],[7] Analysts tend to specialize within one or several industries, and we conjecture that analysts compete within the industry or industries they cover to provide investment value to investor clients. Our objective is to partition companies into the industry groups that are as similar as possible to how they are covered by sell-side analysts. The annual *Institutional Investor* poll asks the buy-side to rate sell-side analysts in roughly 70 industry categories. Therefore, we use the GICS codes at the 59-industry level. This

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[5] We are grateful to the assistance of Validea.com, a now defunct Internet startup company, which provided IBES recommendation data prior to 1996. Using this earlier data, we were able to partition many of the "first" 1996 recommendations into upgrade or downgrade categories.

[6] The Global Industry Classification Standard (GICS) is a joint product, the exclusive property, and service mark of Standard & Poor's and Morgan Stanley Capital International. Complete information is available at www.msci.com and www.standardandpoors.com.

[7] Bhojraj, Lee, and Oler (2002) compare four industry classification schemes: 1) the Standardized Industry Classification (SIC); 2) the North American Industry Classification System (NAICS); 3) Fama-French (1997) groupings; and 4) GICS. The conclude that the GICS classification is superior for identifying firms with the industry peers.

divides the companies in our dataset into 59 distinct industry groups. As shown in Table 1, the largest brokerage firms cover at least one stock in most of the 59 industry groups.

Table 2 shows that the 59-level GICS code partition provides a good proxy for how analysts specialize by industry. Analysts cover 10 companies on average. Using the GICS assignments, the companies they cover fall into 2-3 industries per analyst on average. As a further check, we define the industry into which most the companies the analyst covers fall as the analyst's "most covered" industry. Table 2 shows that the fraction of all companies an analyst covers that are in the analyst's most covered industry averages 0.79 for analysts at the 24 largest brokerage firms and 0.76 for analysts at brokerage firms overall.

[Table 2 about here.]

Table 3 shows descriptive data to provide an indication of variation within and across industries and for three representative industries ("Software", "Hotels Restaurants and Leisure", and "Electric Utilities") and one company in each of the industries. The average number of companies per industry is 204. "Banks" is the largest (and unusual) industry comprising 1,309 companies. All industries have at least some large companies, with the percentage of companies per industry that have CRSP decile 6 or greater ranging from 11.1% to 86.5%. No industry has analyst coverage for every stock, but all industries have at least some analyst coverage. On average, 66.4% of companies within an industry have coverage by at least one analyst. The average analyst coverage per covered company within an industry ranges from 1.5 to 10.7 analysts. Descriptive statistics are shown for each of the 59 industries in Appendix 1 which follows the Tables.

[Table 3 about here.]

The average consensus level for all stocks in all industries is close to a "Buy" (IBES rating level = 2) each month (with little variation). Figure 1 shows consensus levels for each of the 3 example industries from Table 3. As shown in Figure 1, the average consensus level for these three industries varies from 2.0 by less than $\pm$ 0.5. As shown by the spreads between the consensus levels each month for the "best" company (lowest consensus level) and "worst" company (highest consensus level), analysts are willing to differentiate among companies within the industry they follow.[8]

[Figure 1 about here.]

Table 4, Panel A, provides the transition matrix for the recommendations in the dataset. Although buy and strong buy recommendations greatly outnumber underperform and sell recommendations, interestingly, Table 4 shows that downgrades (55.5% of recommendation changes) actually *exceed* upgrades (44.5% of recommendation changes). This suggests a broader universe of stocks is available for long-short portfolio strategies based on recommendation *changes* (e.g., long upgraded stocks and short downgraded stocks) rather than *consensus level* cutoffs (e.g., long "strong buy" and "buy" stocks and short "underperform" and "sell" stocks).

[Table 4 about here.]

It is also worth noting the magnitude of the three-day market-adjusted returns for the various change categories shown in Table 4, Panel B. When a stock is moved to the strong buy (IBES Code "1") category from "buy" or "hold", the average market response is a size-decile-adjusted return of 3%, close to the averages documented for 1989-1991 by Womack (1996). These returns are significantly higher than the 1.06% to 1.48% range reported by Barber et al (2001) for the 1985 to 1996 time period in the Zacks data.

[8] We update the IBES summary month consensus level numbers, which are usually mid-month based, to a calendar-end basis using the daily "Detail" recommendation data.

We offer two possible explanations for the difference. First, the Zacks database, while including most of the significant US brokerage firms, omitted a few large ones. Further, Zacks collected the data second-hand, so that often the dates of the recommendation changes were the dates of written reports that may have been several days after the actual recommendation event. Thus, the averages reported in Barber et al may have included some "event" returns after the actual event dates.

Second, there is some evidence that market responses to new information may have been more intense in the more recent timeframe analyzed here. In some ways, the late 1990s was recognized as the advent of the "day trader" due to convenient and inexpensive transactions services available via the Internet. For example, Busse and Green (2002) show that traders respond to televised analysts' recommendations within a minute of their broadcast in the year 2000.

B. Portfolio Construction

Our first question is whether analysts can and do pick relative winners and losers within their industry specializations. To examine this question, we construct four variants of self-financing portfolios based on analysts' recommendations, as summarized below.

Strategy	Long	Short
Consensus Level #1	Stock with best consensus level in each industry	Stock with worst consensus level in each industry
Consensus Level #2	Stocks with consensus level $\leq$ 1.5	Stocks with consensus level > 3.0
Changes #1	Most net upgraded stock in each industry	Most net downgraded stock in each industry
Changes #2	All net upgraded stocks, equally weighted by industry	All net downgraded stocks, equally weighted by industry

If market participants respond quickly and accurately to changes in analysts' recommendations, then analyst intra-industry stock picking ability will be better measured by upgrade and downgrade activity than by consensus levels. Therefore, we construct portfolios based on recommendation change criteria (Changes Strategies #1 and #2) as well as consensus levels (Consensus Level Strategies #1 and #2).

For each of the portfolio strategies, stocks are selected using information collected during month t - 1 and hence available at the end of month t - 1. We then calculate the one-month holding period return for month t.

In **Consensus Level Strategy #1**, the company with the highest consensus level in each industry is purchased while the one with the worst consensus level in each industry is sold short. If there are ties in the highest or lowest consensus level in an industry, the portfolio is formed by equally weighting the returns of the two or more stocks involved.

Consensus Level Strategy #2 is a consensus-level strategy designed to approximate the Barber, Lehavy, McNichols, and Trueman (2001) strategy (which does not diversify across industries) for the 1996-2001 time frame of our data. In their strategy, they choose for the long side of the portfolio all stocks with a consensus rating of 1.5 or lower (predominantly "strong buy" stocks) and then short all stocks with a level higher than 3.0 ("unattractive" or "sell" stocks). While they rebalance their portfolio daily, our version of their strategy forms the portfolios using their cutoffs at the end of the month.

To examine portfolio strategies based on recommendation *changes*, we define an aggregate change measure. For each stock, using recommendation changes during month t - 1, we calculate an aggregate recommendation change measure ("AgChange"), which is the sum of the number of analyst recommendations which are upgrades plus the number of first recommendations that fall into the IBES buy or strong buy category less the number of downgrades and the first recommendations that are to IBES category hold, underperforform, or sell. Using this simple measure, we refer to stocks with AgChange greater (less) than zero as "net upgraded" ("net downgraded") stocks each month.

For **Changes Strategy #1**, portfolios are constructed by investing long in the stock with the most positive value for AgChange measure and short in the most negative in each industry. When there are ties among stocks for best or worst AgChange measure, which is quite often, we equally weight these companies' returns. **Changes Strategy #2** portfolios are long *all* net upgraded stocks and short *all* net downgraded stocks during the month based on the AgChange measure.

For Consensus Level Strategy #1 and Changes Strategy #1 (when there are ties) and for Changes Strategy #2, the selected stocks are equally-weighted within industries. This is done to prevent recommendations for companies with larger market capitalization from overshadowing recommendations for smaller companies. To prevent industries with many companies from dominating those with few companies, portfolios are also equally weighted by industry. For Consensus Level Strategy #2, stocks are equally weighted in portfolios, but not by industry. Recognizing the potential criticisms of an equal-weighted approach, we form portfolios first by allowing selection from any company in the dataset. We then examine portfolios constrained by decile and by analyst coverage. Appendix 2 provides mathematical notation for return calculations for each of the four strategies.

To be able to examine the link between analyst recommendations and momentum, we construct momentum portfolios in the style of Jegadeesh and Titman (1993). Using geometrically-compound monthly returns for the previous *J* months, we create self-financing portfolios that are long those stocks ranking in the highest 10% of these past returns and short stocks ranking in the lowest 10%. Stock returns are equally weighted in the long and short portfolios. We create, where *K* denotes number of months the portfolio is held consistent with Jegadeesh and Titman, portfolios for J=6/K=1 and J=6/K=6. Both "skip" and "no skip" portfolios are constructed, where "skip" denotes portfolios for which investors are assumed to let a month pass between when stocks are selected from past return rankings and stocks are bought and sold for portfolios.

Because Moskowitz and Grinblatt (1999) note that momentum may be an industry-driven phenomenon, we also construct industry momentum portfolios. Portfolios are created as above except compound returns are calculated for each industry using its monthly return based on an equal weighting of all stocks in that industry that month. All stocks in the 6 industries with the best compound return are purchased, and all the stocks in the 6 industries with the worst returns are sold. Industry returns are equally weighted in the long and short portfolios. Moskowitz and Grinblatt note that industry momentum appears to be a shorter-horizon phenomenon. Therefore, we construct only J=3/K=1 and J=3/K=3 skip and no-skip portfolios.

As for the recommendation portfolios, we form momentum portfolios first by allowing selection from any company in the population. Later, we constrain portfolios by decile and by analyst coverage to examine issues of market efficiency within the "largest" stocks.

II. Recommendation Portfolio Results

Table 5 shows the mean and standard deviation of one-month post-formation returns for each of the recommendation portfolios. In Panel A, we focus on returns when all stocks are available for portfolios, regardless of market capitalization or analyst coverage. Panels B, C, and D provide constrained results, showing the effects of liquidity constraints proxied for by limiting portfolio inclusion to high market cap and analyst coverage.

We also estimate two monthly time-series regressions for each portfolio, as in Barber et al (2001, page 543). First, using portfolio return as the LHS variable, we estimate the three-factor model of Fama and French (1993), where the three factors are 1) the excess market return $(R_m – R_f)$; 2) the return from a value-weighted, self-financing portfolio, which is long small cap stocks and short large cap stocks *(SMB)*; and 3) the return from a value-weighted, self-financing portfolio, which is long value stocks and short growth stocks *(HML)*. Table 5 shows only intercept estimates for this model. Second, we estimate a four-factor model, which is identical to the three-factor model, except an equally-weighted momentum portfolio return is added as the fourth factor *(MOM)*. The momentum portfolio is of Jegadeesh and Titman (1993) design, with $J=11$ and a one month skip. It is long the best 30% and short the worst 30% of stocks. For this model, Table 5 shows our estimates for the intercept plus all four factors.[9]

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[9] We are grateful to Ken French for providing us with this data via his web site at http://mba.tuck.dartmouth.edu. Further details on these factors are also available at that site.

Panel A of Table 5 shows that the mean return from using Consensus Level Strategy #1 is 0.59% in the calendar month following portfolio formation. However, after controlling for the Fama and French three factors, the excess return is 0.41%, and when momentum is also factored out, the return is only 0.13% per month. Neither the mean return nor the intercept estimates are statistically different from zero. Similarly, the mean return and intercept estimates for Consensus Level Strategy #2 in Panel A are also not statistically different from zero. An initial conclusion is that the investor has little to gain from observing a stock's consensus level, which is likely to incorporate recommendations that can have been issued many months prior. This result is not surprising if the value of analyst recommendations is short-lived.

[Table 5 about here.]

It is interesting to note that the ratio of stocks long versus short averages 4:1 in the Consensus Level Strategy #1 portfolios, which is the result of more stocks tying at the best extreme consensus level than at the worst. For the Consensus Level Strategy #2 portfolios, the ratio increases to almost 14:1, which is consistent with analysts' reluctance on average to maintain underperform and sell recommendations during the timeframe we examine.

Panel A shows that Changes Strategies #1 and #2 provide substantially higher returns in the first post-formation month than do the consensus level strategies. Means and intercept estimates are all positive and significant. The standard deviations of monthly returns are also lower than the consensus-level strategies. Estimates for the momentum factor are positive and significant for all portfolio returns. For the changes strategies, the ratio of stocks long versus short is about 1:1, which is consistent with data in Table 4 that show analysts were about equally likely to upgrade or downgrade stocks during the 1996 to 2001:6 timeframe.

Changes Strategy #2, with a mean return of 1.38%, has the lowest standard deviation of monthly returns, at only 1.68%. In fact, while the best one-month return for this strategy is only 5.72%, the worst is only –5.18%. As a robustness check, in results not shown in Table 5, we form portfolios that consist of stocks identical to those of Changes Strategy #2 each month but stocks are equally weighted regardless of industry. Interestingly, returns from these non-industry-diversified portfolios show more volatility and load more heavily on momentum than for Changes Strategy #2.

The results of the comparison the strategies based on consensus *levels* and the strategies based on recommendation *changes* are quite striking and highlight the dissipating nature of the value of analysts' information. A stock's consensus level is the average of all outstanding recommendations and usually does not change considerably from month-to-month. Knowledge that analysts are currently rating a stock a "strong buy" does not suggest measurable out-performance in the future, unless the rating *recently* has been upgraded to "strong buy".[10]

In Table 5, Panel A, we allow investors to construct portfolios unconstrained by liquidity and market capitalization considerations. Therefore, the documented strategy is likely to be unrealizable by large institutional investors, to the extent that small firms' returns contribute significantly to the results. Thus, in Panels B, C, and D, we constrain the allowable stocks available for portfolio formation in three ways.

In Panel B, we eliminate from consideration all stocks in the smallest half of the CRSP size deciles. The remaining stocks (deciles 6 through 10) have market capitalizations of approximately $111 million and above in year-end 2000 dollars. The

[10] By forming portfolios at month-end rather than immediately after recommendation changes obviously biases (lowers) our reported results since recommendation changes occur approximately uniformly distributed within a calendar month. Hence our approach is conservative, in that it measures a first post-event return approximately a half-month after the information event.

changes-based strategies are still valuable but with smaller magnitude than in the unconstrained Panel A. Consensus Level Strategy #1 has a mean return of 0.82%, which is statistically significant, but intercept estimates are not. As in Panel A, Consensus Level Strategy #2 provides little look-ahead value.

In Panel C, we report results for portfolios that are only populated by the largest CRSP decile (10) stocks. This panel represents the ability of analysts to identify mispricing in the largest and most liquid stocks. Again, we find that the returns on the strategies based on consensus ratings levels are not significantly different from zero. For the changes-based strategies, one-month returns are still positive and significant.

In Panel D, we show a different slice, based on the stocks most followed by sell-side analysts. Panel D limits portfolio choice to stocks with at least 15 analysts following them. Constrained to these widely-covered stocks, none of the consensus-level- or change-based strategies have mean returns that are significantly different from zero at conventional levels.

Therefore, the exercise documented in Panels C and D begins to show the limits of analysts' value and the power of competition in the largest, most-followed stocks to eliminate ostensible informational inefficiencies. Naturally, we emphasize that these strategies are not exhaustive and are conservative to one degree in that they wait, on average, a half-month to exploit apparently valuable and dissipating information. And, we also point out that the returns documented are before transactions costs.

Additional analysis for Changes Strategy #2 is shown in Table 6. Consistent with Jegadeesh and Titman (1993), we calculate average monthly returns for Changes Strategy #2 portfolios held for greater than one month. In addition to the one-month holding period (i.e., $K=1$) returns, Table 6 shows mean returns for holding periods of 2, 3, and 6 months. The majority of the market's response to analyst information is in the first month following recommendation changes.

[Table 6 about here.]

Table 6 also shows the decomposition of Changes Strategy #2 returns into their long (Upgraded) and short (Downgraded) components. The returns for these portfolios of upgraded or downgraded stocks are calculated relative to an equally-weighted portfolio of all stocks in the dataset ("market"). Table 6 shows that gains are derived both from being long upgraded stocks and short downgraded stocks.

In detailed work not shown here, we also examined the returns industry by industry for one-month holding period Changes Strategy #2 portfolios unconstrained by market cap or analyst coverage. The returns industry by industry are remarkably consistent. One-month holding period mean returns are positive for 53 of the 59 industries.[11]

Our conclusion from the results in Section II is that analysts definitely are able to distinguish temporarily under- versus over-valued stocks within their followed industries, at least in the short term ranging from 1-3 months. There also appears to be a strong link between returns from recommendation-based strategies and the momentum-return factor of the four-factor model.

III. Momentum Portfolio Results

The means and standard deviations of one-month post-formation returns for the Jegadeesh and Titman (1993) and industry momentum portfolios are shown in Tables 7

[11] The 6 industries with negative mean returns were Auto Components, Household Products, Biotechnology, Diversified Telecommunication Services, Electric Utilities, and Multi-Utilities. The worst mean return was for Auto Components at –0.38%.

and 8 respectively. As in Table 5, Table 7, Panel A provides results when all stocks are available for portfolios while Panels B, C, and D show results constrained when portfolios are limited to stocks with higher market cap and analyst coverage. As in the previous section, we estimate two monthly time-series regressions for each portfolio. Tables 7 and 8 show intercept estimates for the Fama and French three-factor model. For the four-factor model, however, we replace the momentum-return factor *(MOM)* with returns from Changes Strategy #2.

[Tables 7 and 8 about here.]

The first point worth noting is that although the mean returns for the momentum strategies are generally of the same or greater magnitude as that of Changes Strategy #2 discussed in the previous section, the standard deviations are substantially greater. This result is consistent with Grundy and Martin (2001), which documents the risk associated with returns from momentum strategies for 1926-1995. In fact, as shown in Panel A of Tables 7 and 8, when momentum portfolios are formed from all stocks, mean returns are not significantly different from zero.

For comparison, Figure 2 shows monthly returns for Changes Strategy #2, Jegadeesh and Titman momentum (*J=6/K=6*, skip one month), and industry momentum (*J=3/K=3*, skip one month) portfolios. Jegadeesh and Titman (1993, 2001b) document a negative January effect for their momentum strategies for the 1965-1998 timeframe. Grundy and Martin (2001) document a strong negative January effect that sharply reduces the overall returns from Jegadeesh and Titman momentum portfolios for the period 1926-1995. Interestingly, as shown in Figure 2, the January effect continues in

1997-2001: every January return for the Jegadeesh and Titman portfolio is negative.[12] In contrast, the Changes Strategy #2 portfolio returns avoid the January seasonal effect.

Another important result is that every one of the momentum portfolios, regardless of market cap or analyst coverage constraint, loads significantly on the recommendation-return factor. The momentum return factor used in the previous section was a Jegadeesh and Titman-style strategy with a longer look-back period (*J=11*) and coarser filter (best 30% - worst 30%) than used here. Table 7 shows that the link between recommendation portfolio returns and momentum returns holds up for shorter *J* and finer filter (best 10% - worst 10%). As shown in Table 8, the link between recommendation returns and momentum also holds for industry-based strategies with an even shorter *J*.

IV. Further Investigation into the Link between Recommendations and Momentum

The estimates from the four-factor models in Sections II and III suggest a strong link between analyst information and momentum. We now examine this connection.

A. Do analyst recommendations impact stock selection for momentum portfolios?

An interesting question is whether the stocks recently upgraded or downgraded by analysts are more likely to be included in momentum-based portfolios than stocks without recent recommendation changes. As documented in Section II, the value from recommendation changes is fairly short-lived, dissipating in 2-3 months. Are these returns large enough to pull the stocks into the Jegadeesh and Titman *J=6* momentum portfolios?

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[12] Consistent with January 1996 as the first month in our sample with recommendation data, the first post-formation month return in our sample is February 1996. Thus, we do not estimate January 1996 returns for any of the portfolios.

To answer examine this question, we perform chi-square tests of the null hypothesis that the probability of stock selection for momentum portfolios is not correlated with the net upgrade or net downgrade of a stock. Specifically we condition on stocks net upgraded or net downgraded in the most recent month used to calculate the *J=6* compound returns used as the criteria for momentum portfolio stock selection. The results are provided in the upper half of Table 9. The *p*-values (<.0001) indicate that we reject the null hypothesis of randomness for each panel. Unconditionally, the probabilities of a stock's being selected for momentum portfolio purchase or sale are 10% each. As shown in Table 9, net upgrading a stock increases the probability that it will be selected for purchase in the momentum portfolio and decreases the probability it will be shorted. Similarly, net downgrading a stock decreases the probability it will be purchased and increases the probability it will be sold short.

[Table 9 about here.]

B. Does stock selection for momentum portfolios impact analyst recommendations?

Perhaps an even more interesting question is whether analysts recommend stocks that meet the cutoffs for momentum portfolios. We use the Jegadeesh and Titman *J=6* portfolios that have a one-month skip between stock selection and trade execution. We perform chi-square tests, conditioning on stocks that are net upgraded or net downgraded in the "skip" month. The results are shown in the lower half of Table 9.

As shown in Panel A, when we look at the stocks of all 12,028 in the dataset, the probability of net upgrade in a month is 10.6% and the probability of net downgrade is 6.9%. Stocks that meet the criteria for inclusion in the short side of the momentum portfolio are more likely to be net downgraded and less likely to be net upgraded. Stocks that make the cutoff for the long side of the portfolio are more likely to be upgraded. These results are consistent with the possibility that at least some analysts, aware that the momentum phenomenon exists, stack the cards in their favor by using this information as a factor in making their recommendation decisions. Interestingly, meeting the criteria for the long side of the momentum portfolio has little impact on the probability that the stock will be net downgraded, however. As shown in Panels B-D, these results continue to hold when we examine larger and more widely covered stocks.

C. What are recommended stocks' contributions to momentum portfolio returns?

We are interested in assessing the magnitude of the contribution of the returns from recommended stocks to momentum portfolio returns. As an approximation, we calculate separately the mean returns for stocks in the long and short sides of the momentum portfolios conditional on whether those stocks were net upgraded, downgraded, or neither. We use the Jegadeesh and Titman *J=6/K=1* portfolios that have a one-month skip between stock selection and trade execution. We use the stock's upgrade, downgrade, or unchanged status during the "skip" month. As shown in Table 10, upgraded stocks accounted for 14% of the stocks that met the cutoff for the long side of momentum portfolios during the timeframe. The mean return for these stocks in the calendar month following their net upgrade was 3.8%. This accounted for a contribution of 0.54% toward the momentum portfolio strategy's 1.59% mean one-month return, or 34% (=0.54%/1.59%). When the returns from net downgraded stocks are included, upgraded stocks in the long side and downgraded stocks in the short side of the momentum portfolio account for 37% of the one-month momentum return.[13]

[Table 10 about here.]

[13] Our approach equal weights the stocks in each category over the entire timeframe. As the result of IPOs and de-listings during the sample period, the number of stocks in momentum portfolios varies from month to month. Therefore, the best-worst return of 1.59% in Table 10 differs slightly from that of 1.63% in Table 7.

V. Conclusions

We document in this study that analyst information, processed at the industry level, is quite useful in explaining future returns. First, our evidence suggests that analysts are indeed able to distinguish between future outperforming and underperforming stocks within their followed industry. Using analysts' recommendation changes each calendar month, long-short portfolios equally-weighted by industry earn an average of 1.4% in the next month. Perhaps more interestingly, these portfolio returns are substantially less volatile than momentum portfolios during the period of our sample.

We also examine the link between analyst recommendations and price momentum. All of the recommendation portfolios we examine load heavily on our recommendation portfolio return factor. Stocks are more likely to be included in momentum portfolios following analysts' recommendations, and analysts are more likely to recommend momentum stocks. Returns from recently recommended stocks account for about a third of the returns of the typical price momentum strategy.

Our findings suggest several areas for future research. First, we have done little to try to optimize a recommendation-based strategy. For example, because we form portfolios once at the end of each month, we fail to capture, on average, two weeks of price reaction immediately following recommendation changes. In fact, this time period may offer the greatest opportunities to investors who want to capture the value of analyst recommendations. Future research could examine the effects of more frequent rebalancing. Also, we have used a simple summation of upgrades and downgrades without differentiating among the level changed to or from. Nor have we differentiated among analysts by reputation or firm. Another area for possible optimization is suggested by interesting new research by Ivkovic and Jegadeesh (2002), who document that price reactions to analyst recommendations generally increase with time from the last scheduled earnings announcement, consistent with analysts' ability to independently gather non-public information. They find that the exception in price reaction is for downgrades in the few weeks prior to the next scheduled earnings announcement, consistent with company management incentives to release bad news slowly. Recommendation-change portfolio strategies that condition or weight changes by proximity to earnings announcements might yield even better returns.

Another avenue for future research planned by these authors is to examine whether competition among analysts within industries leads to valuable signals for sector rotation strategies. For example, aggregating recommendation changes industry by industry could be examined for possible value in determining in-favor and out-of-favor industries and for understanding the industry momentum documented by Moskowitz and Grinblatt (1999).

References

Badrinath, S.G., and Sunil Wahal, 2002, Momentum Trading by Institutions, *The Journal of Finance* 57 (No 6): 2449-2478.

Barber, Brad, Reuven Lehavy, Maureen McNichols, and Brett Trueman, 2001, Can Investors Profit from the Prophets? Security Analyst Recommendations and Stock Returns, *The Journal of Finance* 56 (No 2):531-563.

Barber, Brad, Reuven Lehavy, Maureen McNichols, and Brett Trueman, 2002, Prophets And Losses: Reassessing the Returns To Analysts' Stock Recommendations, forthcoming, *Financial Analysts Journal.*

Bhojraj, Sanjeev, Charles M. C. Lee, and Derek K. Oler, 2002, What's My Line? A Comparison of Industry Classification Schemes for Capital Market Research, working paper, Cornell University.

Boni, Leslie, and Kent L. Womack, 2002a, Wall Street's Credibility Problem: Misaligned Incentives and Dubious Fixes? *Brookings-Wharton Papers on Financial Services,* 93-130.

Boni, Leslie, and Kent L. Womack, 2002b, Solving the Sell-Side Research Problem: Insights from Buy-Side Professionals, working paper, University of New Mexico and Dartmouth College.

Busse, Jeffrey A., and T. Clifton Green, 2002, Market efficiency in real time, *Journal of Financial Economics*, 65: 415-437.

Chen, Hsiu-Lang, Narasimhan Jegadeesh, and Russ Wermers, 2000, The Value of Active Mutual Fund Management: An Examination of the Stockholdings and Trades of Fund Managers, *Journal of Financial and Quantitative Analysis* 35, 343-368.

Fama, Eugene, and Kenneth French, 1993, Common Risk Factors in the Returns on Stocks and Bonds, *Journal of Financial Economics*, 33, 3-56.

Gleason, Cristi, and Charles M.C. Lee, 2002, Analyst Forecast Revisions and Market Price Discovery, working paper, Cornell University.

Grinblatt, Mark, Sheridan Titman, and Russ Wermers, 1995, Momentum Investment Strategies, Portfolio Performance and Herding: A Study of Mutual Fund Behavior, *American Economic Review* 85, 1088-1105.

Grundy, Bruce D., and J. Spencer Martin, 2001, Understanding the Nature of the Risks and The Source of the Rewards to Momentum Investing, *Review of Financial Studies* 14, 29-79.

Hong, Harrison, and Jeremy C. Stein, 1999, A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets, *Journal of Finance* 54, 2143-2184.

Hong, Harrison, Terence Lim, and Jeremy C. Stein, 2000, Bad News Travels Slowly: Size, Analyst Coverage, and the Profitability of Momentum Strategies, *Journal of Finance*, LV, 265-295.

Ivkovic, Zoran, and Narasimhan Jegadeesh, 2002, The Timing and the Value of Forecast and Recommendation Revisions: Do Analysts Receive Early Peek at Good News?, working paper, Emory University.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65-91.

Jegadeesh, Narasimhan, and Sheridan Titman, 2001a, Momentum, working paper, University of Illinois and University of Texas.

Jegadeesh, Narasimhan, and Sheridan Titman, 2001b, Profitability of Momentum Strategies: An Evaluation of Alternative Explanations, *Journal of Finance* 56, 699-720.

Jegadeesh, Narasimhan, Joonghyuk Kim, Susan D. Krische, and Charles M.C. Lee, 2002, Analyzing the Analysts: When Do Recommendations Add Value?, working paper, Cornell University.

Krigman, Laurie, Wayne Shaw, and Kent L. Womack. 1999. Why Do Firms Switch Underwriters?, *Journal of Financial Economics* 60: 245-284.

Moskowitz, Tobias J., and Mark Grinblatt, 1999, Do Industries Explain Momentum?, *Journal of Finance* 54, 1249-1290.

Stickel, Scott E. 1995. The Anatomy of the Performance of Buy and Sell Recommendations. *Financial Analysts Journal* Sept-Oct 1995:25-39.

Womack, Kent L, 1996, Do Brokerage Analysts' Recommendations Have Investment Value? *Journal of Finance* L1 (no.1):137-167.

Figure 1
Time Series Variation in Industry and Stock Consensus Rating Levels

Figure 1 shows the consensus (average) level of analyst ratings in 3 example S&P/MSCI GICS industry categories for January 1996 to June 2001, where 1 = strong buy, 2 = buy, 3 = hold, 4 = underperform, and 5 = sell. The average consensus level for the market as a whole is very close to 2.0 for the entire time period. The graphs below show the consensus level each month for the "best" and "worst" company (which changes through time), the average for all companies in the industry, and a sample company.

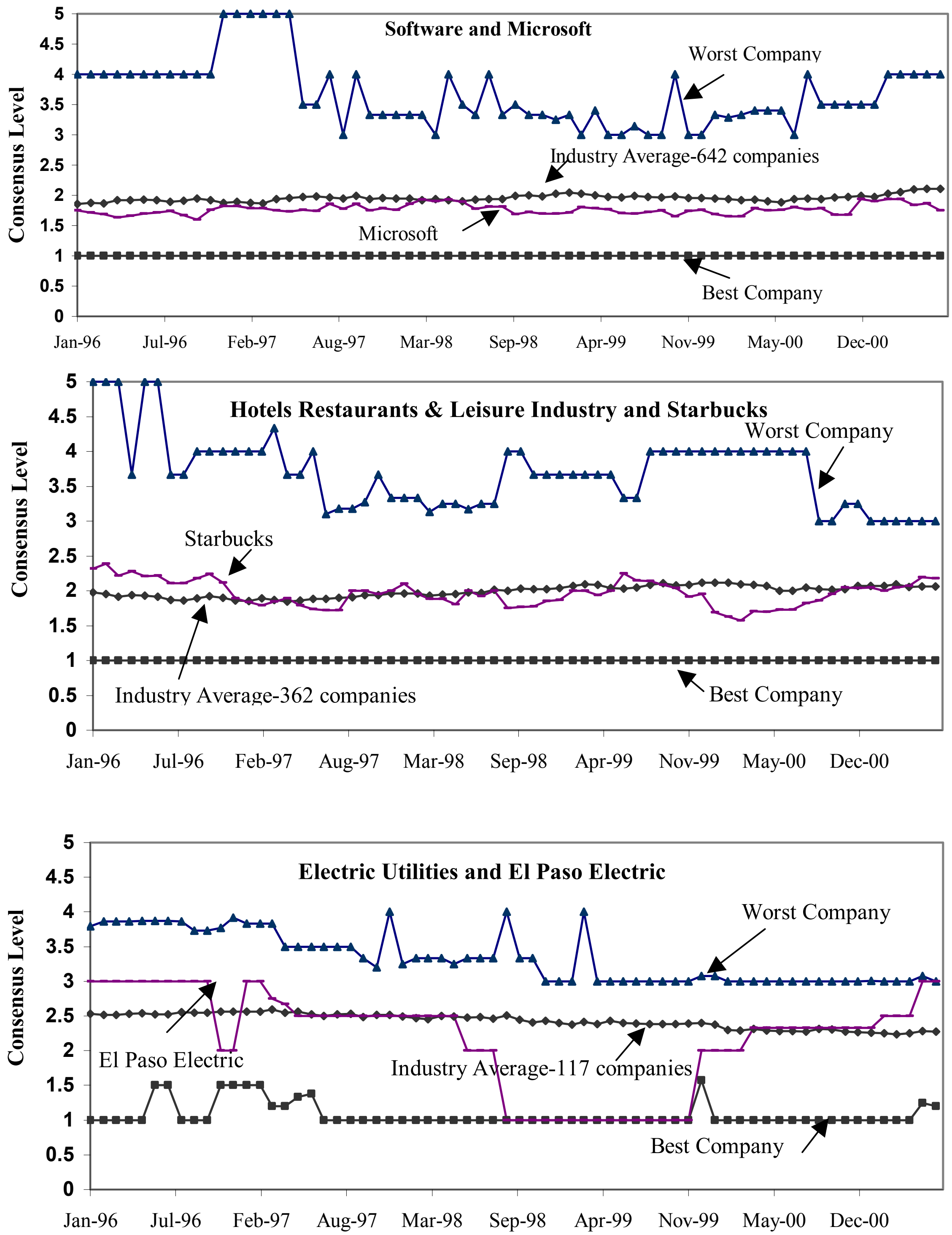

Figure 2
Time Series Returns from Recommendation and Momentum Portfolios

Figure 2 shows the time-series of one-month returns from portfolios formed using recommendation-change and price momentum strategies. Recommendation-change portfolios are industry-diversified self-financing portfolios, long net upgraded stocks and short net downgraded stocks. Jegadeesh and Titman (1993) momentum portfolios are J=6/K=6, best 10% stocks minus worst 10% stocks, skip 1 month, portfolios. Industry portfolios are J=3/K=3, best 10% industries minus worst 10% industries, skip 1 month, portfolios. Stocks can be chosen from all NYSE/AMEX/Nasdaq stocks.

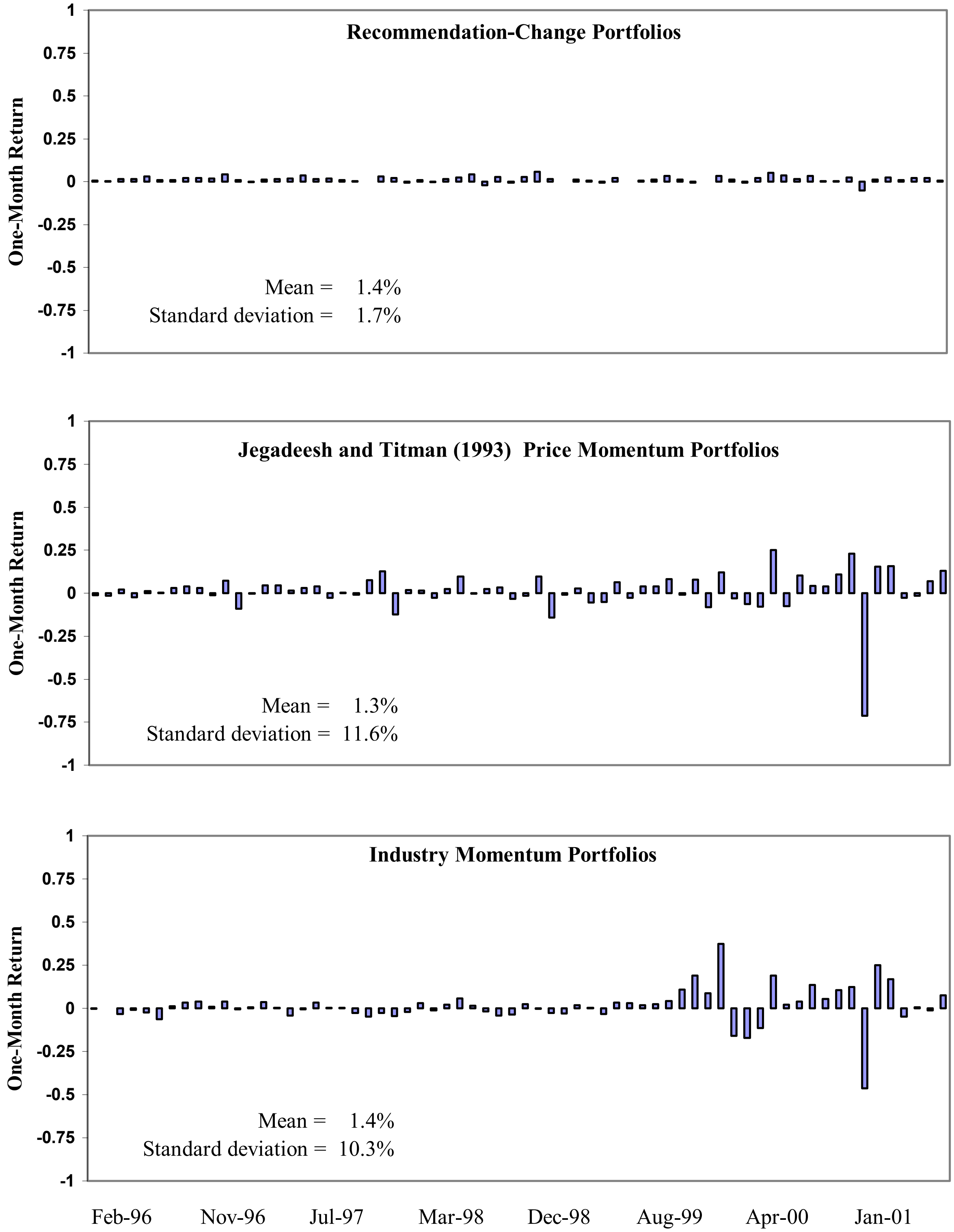

Table 1
Brokerage Firm Characteristics

The data on analyst recommendation changes shows 151,667 recommendation changes by sell-side analysts in the time period January 1996 to June 2001. Table 1 shows the number of companies and S&P/MSCI GICS industries followed by the largest 24 U.S. brokerage houses as well as the remaining 409 brokerage firms and subsidiaries separately listed in IBES. For the time frame above, column 4 gives the total number of analyst IDs listed in IBES. When an analyst changes firms, he or she may be counted separately by the other brokerage firm. Therefore, the analyst count is almost surrely an overestimate of the antual number of analysts working at sell-side firms.

	BrokerName	**Companies followed**	**Industries followed**	**Analysts 1996-2001**	**Number of Recommendations**
	(1)	(2)	(3)	(4)	(5)
1	Salomon Smith Barney	2,412	59	378	6,548
2	Merrill Lynch	2,125	57	374	4,959
3	Deutsche Banc Alex Brown	2,045	56	306	5,360
4	Morgan Stanley	1,824	57	251	4,750
5	Credit Suisse First Boston	1,813	57	259	3,705
6	Goldman Sachs	1,651	57	191	3,744
7	Lehman Brothers	1,648	54	207	3,111
8	Donaldson	1,625	58	118	3,696
9	Banc of America Scurities	1,581	55	158	3,457
10	UBS Warburg	1,473	57	214	2,903
11	CIBC World Markets	1,454	56	162	2,829
12	Bear Stearns	1,447	54	154	2,890
13	Prudential Securities	1,295	53	131	3,166
14	J.P. Morgan	1,276	53	192	2,348
15	Robertson Stephens	1,195	50	131	2,920
16	Paine Webber	1,124	55	107	2,587
17	Dain Rauscher Wessels	1,080	52	105	2,444
18	A.G. Edwards & Sons	1,029	55	91	3,231
19	ABN AMRO	990	55	96	1,915
20	ING Baring Furman Selz	890	54	105	1,866
21	First Union Securities	890	50	89	1,827
22	Chase H&Q	853	37	82	1,683
23	U.S. Bancorp Piper Jaffr	833	49	69	1,858
24	Schroder	745	53	79	1,605
25+	Remaining 409 Brokers & Subs	7,179	59	3,874	76,265
	Total, all Brokerage Firms	**7,766**	**59**		**151,667**

Table 2
Analyst Coverage by Stocks and Industry, 1996 to 2001:6

For January 1996 through June 2001, this table shows descriptive statistics for analyst coverage by company and by industry. Panel A shows statistics for analysts at the 24 brokerage firms that cover the most companies. Panel B provides data for analysts at all brokerage firms. In each panel, analysts are further broken out by the number of companies he or she covers in the 1996 through 2001:6 timeframe, with column 1 showing the number of analysts in each category. Columns 2 and 3 show the average number of companies and S&P/MSCI GICS industries per analyst. For each analyst, the industry with the greatest number of companies that analyst covers is defined as his or her "most covered" industry. The number of companies within the analyst's most covered industry is divided by the total number of companies that analyst covers. Columns 4-7 indicate for each analyst category the mean, median, and 25th-percentile and 75th-percentile points for this fraction. Column 8 shows the total number of recommendations made by analysts in each analyst category during January 1996 through June 2001.

	Number of Analysts (1)	Companies Covered per Analyst (mean) (2)	Industries Covered per Analyst (mean) (3)	Number of Companies Analyst Covers in Most Covered Industry/ Number of Companies the Analyst Covers (mean) (4)	(median) (5)	(25%-ile) (6)	(75%-ile) (7)	Number of Recommendation Changes (8)
Panel A: Top 24 Brokerage Firms								
Analyst Covers:								
1-10 companies	2,595	4.4	1.7	0.84	1.00	0.67	1.00	16,735
11-20 companies	1,007	14.9	3.2	0.73	0.80	0.55	0.93	27,492
21-30 companies	334	24.7	4.2	0.72	0.74	0.55	0.90	16,528
31-40 companies	106	34.5	5.3	0.66	0.68	0.53	0.84	7,532
> 40 companies	71	64.4	12.2	0.52	0.55	0.20	0.82	7,116
All	4,113	10.4	2.6	0.79	0.88	0.62	1.00	75,403
Memo: Companies covered	5,979							
Panel B: All Brokerage Firms								
Analyst Covers:								
1-10 companies	6,087	4.1	1.9	0.81	1.00	0.60	1.00	37,859
11-20 companies	1,952	14.7	3.9	0.67	0.69	0.46	0.91	53,386
21-30 companies	609	24.6	5.3	0.65	0.67	0.46	0.87	30,815
31-40 companies	211	34.6	6.3	0.62	0.66	0.42	0.82	14,698
> 40 companies	134	62.1	11.5	0.50	0.48	0.21	0.79	14,909
All	8,993	9.7	2.8	0.76	0.83	0.50	1.00	151,667
Memo: Companies covered	7,766							

Table 3
Descriptive Statistics and Examples for Industries

Table 3 shows summary statistics for the 59 S&P/MSCI GICS industries along with 3 example industries and example companies. Column 1 shows that the number of companies per industry ranges from 9 (Transportation Infrastructure) to 1,309 (Banks), with a mean of 204 companies per industry. Column 2 shows the percentage of companies within the industry with a CRSP size decile of 6 or greater. Column 3 shows the percentage of companies within the industry that have the coverage of at least one analyst during the January 1996 through June 2001 timeframe. Column 4 indicates the average number of analysts per covered company within the industry. Column 5 shows the average number of recommendations per covered company during January 1996 through June 2001. Appendix 1 lists column 1-5 statistics separately for each of the 59 industries.

	Number of Companies (1)	Companies with Decile of 6 or more (2)	Companies Covered by Analysts (3)	Average Analysts per Covered Company (4)	Average Recommendations per Covered Company (5)
Summary Statistics for All Industries					
Mean	204	44.9%	66.4%	4.9	20.3
Maximum	1,309	86.5%	88.2%	10.7	32.4
Minimum	9	11.1%	22.2%	1.5	6.3
Example Industries:					
Software	642	39.9%	72.9%	4.3	18.3
Example Company: Microsoft		Decile = 10		32	146
Hotels Restaurants & Leisure	362	35.1%	59.1%	4.4	19.8
Example Company: Starbucks		Decile = 10		17	117
Electric Utilities	117	76.9%	86.3%	8.4	28.3
Example Company: El Paso Electric Co.		Decile = 8		2	7

Table 4
Transition Matrix of Recommendations and Three-Day Event Excess Returns, 1996 to 2001:06

Panel A shows the number of analyst recommendations as categorized by IBES, where 1 = strong buy, 2 = buy, 3 = hold, 4 = underperform, and 5 = sell. Rows 1-5 report recommendations that are changes from one category to another. Row 6 reports recommendations that are the first observation of an analyst at a brokerage firm for a particular stock. Panel B reports the means of percentage 3-day event excess returns for the recommendation categories in Panel A. The three-day event return is the geometrically cumulated return for the day before, day of, and day after the recommendation. The excess return is the raw stock return less the appropriate size-decile return of the equal-weighted CRSP NYSE/AMEX/Nasdaq index. Excess return means that are significantly different from zero at the 10% level are shown in bold.

Panel A: Number of Recommendations

From IBES Code \ To IBES Code	1	2	3	4	5	All
1	na	15,676	9,681	195	236	25,788
2	15,078	na	17,898	450	218	33,644
3	6,234	13,386	na	1,322	892	21,834
4	101	316	1,147	na	105	1,669
5	127	105	827	106	na	1,165
First Recommendation	22,429	28,170	15,857	636	475	67,567
All	43,969	57,653	45,410	2,709	1,926	151,667

Panel B: 3-Day Event Mean Returns

From IBES Code \ To IBES Code	1	2	3	4	5
1	na	**-4.53%**	**-6.77%**	**-7.24%**	**-3.74%**
2	**3.17%**	na	**-5.64%**	**-5.83%**	**-4.95%**
3	**2.96%**	**3.02%**	na	**-2.30%**	**-3.60%**
4	**3.20%**	**3.06%**	**1.32%**	na	**-3.95%**
5	1.13%	0.52%	**1.40%**	-0.66%	na
First Recommendation	**1.88%**	**0.44%**	**-1.83%**	**-2.80%**	**-1.56%**

Table 5
Percentage Monthly Returns and Regression Estimates for Recommendation Strategy Portfolios, 1996 to 2001:6

This table shows percentage monthly returns (column 1), standard deviations (column 2), and estimates from time-series regressions of calendar-time portfolios formed using recommendation strategies as discussed in Section I.B. Column 3 shows the intercept from the Fama and French 3-factor model. Columns 4-8 show estimates for the 4-factor model. Panel A shows results when stocks can be selected for portfolios regardless of market cap or analyst coverage. Panels B and C show results when stocks are restricted by CRSP market cap decile to $\geq$ 6 and 10 respectively. Panel D shows results when stocks are restricted to analyst coverage of 15 and higher. T-statistics in **bold** indicate estimates that are significant at the 10% level. Columns 9 and 10 show the average number of stocks long and short per month.

	Mean Return (1)	Std. Dev. (2)	Intercept from F&F (3)	Intercept from 4-Factor (4)	Coefficient Estimate for 4-Factor Model Rm - Rf (5)	SMB (6)	HML (7)	MOM (8)	Stocks Long (9)	Stocks Short (10)
Panel A: Portfolios Chosen from All Stocks										
Consensus Level Strategy #1: Best - Worst	0.585	3.75	0.408	0.013	0.212	0.005	0.207	0.292	525	133
	1.27		*0.84*	*0.03*	***1.77***	*0.05*	*1.41*	***4.14***		
Consensus Level Strategy #2: Cons. Lev. $\leq$ 1.5 - Cons. Lev. > 3	0.593	5.71	0.393	-0.273	0.341	0.220	0.136	0.491	1,250	91
	0.84		*0.57*	*-0.46*	***2.15***	*1.54*	*0.70*	***5.26***		
Changes Strategy #1: Best - Worst	1.506	2.87	1.415	1.197	0.116	0.085	0.103	0.161	123	119
	4.26		***3.82***	***3.33***	*1.20*	*0.98*	*0.87*	***2.82***		
Changes Strategy #2: All Net Upgraded - All Net Downgraded	1.379	1.68	1.321	1.097	0.094	-0.002	0.069	0.162	792	515
	6.67		***6.01***	***5.98***	***1.90***	*-0.05*	*1.14*	***5.57***		
Panel B: Portfolios Chosen from Stocks with Market Capitalization of CRSP Decile 6 or Greater										
Consensus Level Strategy #1: Best - Worst	0.818	3.33	0.567	0.221	0.321	0.139	0.185	0.255	230	101
	1.99		*1.43*	*0.62*	***3.38***	*1.63*	*1.58*	***4.56***		
Consensus Level Strategy #2: Cons. Lev. $\leq$ 1.5 - Cons. Lev. > 3	0.830	5.86	0.836	0.310	0.278	0.229	-0.328	0.388	773	53
	1.15		*1.48*	*0.63*	***2.11***	***1.94***	***-2.03***	***5.02***		
Changes Strategy #1: Best - Worst	1.351	3.04	1.250	1.017	0.119	0.159	0.131	0.172	114	108
	3.61		***3.27***	***2.75***	*1.20*	***1.79***	*1.08*	***2.95***		
Changes Strategy #2: All Net Upgraded - All Net Downgraded	1.063	1.68	1.026	0.837	0.062	0.036	0.048	0.139	670	437
	5.13		***4.73***	***4.33***	*1.19*	*0.77*	*0.80*	***4.56***		

Table 5 (continued)
Percentage Monthly Returns and Regression Estimates for Recommendation Strategy Portfolios, 1996 to 2001:6

	Mean Return (1)	Std. Dev. (2)	Intercept from F&F (3)	Intercept from 4-Factor (4)	Coefficient Estimate for 4-Factor Model Rm - Rf (5)	SMB (6)	HML (7)	MOM (8)	Stocks Long (9)	Stocks Short (10)
Panel C: Portfolios Chosen from Stocks with Market Capitalization of CRSP Decile 10										
Consensus Level Strategy #1: Best - Worst	0.123	2.75	0.027	-0.173	0.169	0.097	0.012	0.147	55	56
	0.36		*0.08*	*-0.55*	***1.99***	*1.27*	*0.11*	***2.95***		
Consensus Level Strategy #2: Cons. Lev. ≤ 1.5 - Cons. Lev. > 3	0.004	10.70	0.135	-0.260	0.342	0.591	-0.804	0.291	84	10
	0.00		*0.14*	*-0.27*	*1.32*	***2.54***	***-2.53***	***1.91***		
Changes Strategy #1: Best - Worst	0.545	2.34	0.498	0.405	0.067	-0.002	0.030	0.069	70	65
	1.89		*1.62*	*1.29*	*0.80*	*-0.03*	*0.29*	*1.40*		
Changes Strategy #2: All Net Upgraded - All Net Downgraded	0.487	1.67	0.480	0.419	0.042	-0.042	-0.038	0.045	216	151
	2.37		***2.22***	***1.90***	*0.72*	*-0.80*	*-0.52*	*1.29*		
Panel D: Portfolios Chosen from Stocks with Coverage of at Least 15 Analysts										
Consensus Level Strategy #1: Best - Worst	0.379	4.13	0.269	-0.292	0.268	-0.164	-0.008	0.413	42	42
	0.75		*0.52*	*-0.70*	***2.39***	*-1.63*	*-0.06*	***6.27***		
Consensus Level Strategy #2: Cons. Lev. ≤ 1.5 - Cons. Lev. > 3	1.418	15.67	0.661	0.099	1.139	-0.670	0.040	0.415	30	4
	0.74		*0.34*	*0.05*	***2.16***	*-1.41*	*0.06*	*1.34*		
Changes Strategy #1: Best - Worst	0.172	2.80	0.207	-0.001	-0.014	-0.053	-0.024	0.190	46	44
	0.50		*0.56*	*-0.15*	*0.15*	*-0.63*	*-0.21*	***3.47***		
Changes Strategy #2: All Net Upgraded - All Net Downgraded	0.224	2.18	0.275	0.063	-0.001	-0.129	-0.056	0.156	136	102
	0.84		*0.97*	*0.24*	*-0.02*	***-2.02***	*-0.64*	***3.73***		

Table 6
Further Examination and Robustness Checks, Calendar Monthly Returns, 1996 to 2001:6

This table shows percentage monthly returns, t-statistics,and standard deviations for Changes Strategy #2 portfolios. Consistent with Table 5, Panel A, Changes Strategy #2 portfolios are long all stocks that were net upgraded in the previous month and short all stocks that were net downgraded in the previous month. Portfolios are equally-weighted within and across industries, as described in Section I.B. Panel B shows returns for Changes Strategy #2 portfolios when stocks are constrained to a market capitalization of CRSP decile 6 or greater. Row 1 of each panel shows the returns for the portfolios. Then the portfolios are decomposed into their long ("Upgraded Portfolio") and short ("Downgraded Portfolio") components relative to an equally-weighted portfolio of all stocks in the dataset ("Market"). Column 1 shows results for portfolios with one-month holding periods, consistent with Table 5. Columns 2, 3, and 4 show average monthly returns for holding periods of 2, 3, and 6 months, respectively, consistent with Jegadeesh and Titman (1993).

	Mean Monthly Return: One-Month Hold. Period (1)	**Mean Monthly Return: Two-Month Hold. Period (2)**	**Mean Monthly Return: Three-Month Hold. Period (3)**	**Mean Monthly Return: Six-Month Hold. Period (4)**
Panel A: Portfolios Chosen from All Stocks				
Upgraded minus Downgraded Portfolio:				
Mean return, %	1.379	0.860	0.659	0.363
T-statistic	***6.67***	***4.95***	***3.75***	***2.31***
Standard deviation, %	1.68	1.40	1.41	1.22
Upgraded Portfolio minus Market:				
Mean return, %	0.606	0.342	0.234	0.150
T-statistic	*1.57*	*0.90*	*0.61*	***3.78***
Standard deviation, %	3.14	3.06	3.07	3.10
Downgraded Portfolio minus Market:				
Mean return, %	-0.773	-0.517	-0.422	-0.209
T-statistic	***-2.18***	*-1.49*	*-1.24*	*-0.61*
Standard deviation, %	2.88	2.79	2.73	2.70
Panel B: Portfolios Chosen from Stocks with Market Capitalization of CRSP Decile 6 or Greater				
Upgraded minus Downgraded Portfolio:				
Mean return, %	1.063	0.621	0.397	0.218
T-statistic	***5.13***	***3.75***	***2.31***	*1.43*
Standard deviation, %	1.68	1.33	1.37	1.20
Upgraded Portfolio minus Market:				
Mean return, %	0.482	0.295	0.180	0.152
T-statistic	*1.09*	*0.69*	*0.41*	*0.34*
Standard deviation, %	3.60	3.46	3.51	3.51
Downgraded Portfolio minus Market:				
Mean return, %	-0.580	-0.326	-0.211	-0.063
T-statistic	*-1.34*	*-0.79*	*-0.53*	*-0.16*
Standard deviation, %	3.51	3.32	3.19	3.14

Table 7

Percentage Monthly Returns and Regression Estimates for Jegadeesh and Titman-Style Momentum Portfolios, 1996 to 2001:6

This table shows percentage monthly returns (column 1), standard deviations (column 2), and estimates from time-series regressions of calendar-time portfolios formed using price momentum strategies, as discussed in Section I.B. Stocks are ranked using their geometrically-compound monthly returns for the past *J* months. Portfolios are long stocks ranking in the highest 10% of these past returns and short stocks ranking in the lowest 10%. Stock are equally weighted in the long and short portfolios. We create, where *K* denotes number of months the portfolio is held consistent with Jegadeesh and Titman (1993), portfolios for *J=6/K=1* and *J=6/K=6* . Both "skip" and "no skip" portfolios are constructed, where "skip" denotes portfolios for which investors let a month pass between when stocks are selected from past return rankings and stocks are bought and sold for portfolios. Column 3 shows the intercept from the Fama and French 3-factor model. Columns 4-8 show estimates for the 4-factor model, where the 4th factor is the return from recommendation-based Change Strategy #2. Panel A shows results when stocks can be selected for portfolios regardless of market cap or analyst coverage. Panels B and C show results when stocks are restricted by CRSP market cap decile to ≥ 6 and 10 respectively. Panel D shows results when stocks are restricted to analyst coverage ≥ 15. T-statistics in **bold** indicate significance at the 10% level.

	Mean Return	Std. Dev.	Intercept from		Coefficient Estimate for 4-Factor Model			
			F&F	4-Factor	Rm - Rf	SMB	HML	Rec. Fac.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Portfolios Chosen from All Stocks								
Jegadeesh and Titman-Style Momentum Strategy, J=6/K=1, Skip 1 month	1.634	13.99	1.023	-5.446	-0.095	0.644	0.964	4.914
	0.95		*0.58*	***-3.05***	*-0.24*	***1.86***	***2.02***	***5.96***
Jegadeesh and Titman-Style Momentum Strategy, J=6/K=6, Skip 1 month	1.304	11.64	0.862	-4.514	-0.033	0.191	0.540	4.083
	0.91		*0.57*	***-2.91***	*-0.10*	*0.64*	*1.30*	***5.71***
Jegadeesh and Titman-Style Momentum Strategy, J=6/K=1, No Skip	0.013	15.94	-0.350	-7.291	-0.376	0.727	0.787	5.273
	0.01		*-0.17*	***-3.46***	*-0.81*	***1.78***	*1.40*	***5.42***
Jegadeesh and Titman-Style Momentum Strategy, J=6/K=6, No Skip	1.146	12.84	0.662	-5.243	-0.085	0.360	0.683	4.486
	0.73		*0.40*	***-3.10***	*-0.23*	*1.10*	*1.51*	***5.74***
Panel B: Portfolios Chosen from Stocks with Market Capitalization of CRSP Decile 6 or Greater								
Jegadeesh and Titman-Style Momentum Strategy, J=6/K=1, Skip 1 month	3.715	12.11	3.786	-0.896	-0.539	0.740	0.251	3.557
	2.49		***2.53***	*-0.55*	*-1.51*	***2.34***	*0.58*	***4.74***
Jegadeesh and Titman-Style Momentum Strategy, J=6/K=6, Skip 1 month	2.479	11.94	2.398	-3.104	-0.321	0.255	0.128	4.180
	1.69		*1.54*	***-1.94***	*-0.91*	*0.82*	*0.30*	***5.65***
Jegadeesh and Titman-Style Momentum Strategy, J=6/K=1, No Skip	2.298	12.98	2.605	-2.391	-0.782	0.713	0.050	3.795
	1.44		*1.63*	*-1.38*	***-2.05***	***2.12***	*0.11*	***4.75***
Jegadeesh and Titman-Style Momentum Strategy, J=6/K=6, No Skip	2.507	12.92	2.461	-3.474	-0.437	0.371	0.201	4.509
	1.58		*1.47*	***-2.03***	*-1.16*	*1.11*	*0.44*	***5.69***

Table 7 (continued)
Percentage Monthly Returns and Regression Estimates for Jegadeesh and Titman-Style Momentum Portfolios, 1996 to 2001:6

	Mean Return	Std. Dev.	Intercept from		Coefficient Estimate for 4-Factor Model			
			F&F	4-Factor	Rm - Rf	SMB	HML	Rec. Fac.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel C: Portfolios Chosen from Stocks with Market Capitalization of CRSP Decile 10								
Jegadeesh and Titman-Style Momentum Strategy, J=6/K=1, Skip 1 month	2.986	12.71	3.135	-1.022	-0.632	0.976	0.291	3.158
	1.91		***2.07***	*-0.60*	***-1.68***	***2.93***	*0.64*	***3.98***
Jegadeesh and Titman-Style Momentum Strategy, J=6/K=6, Skip 1 month	2.438	10.32	2.600	-1.586	-0.452	0.494	-0.087	3.180
	1.92		***2.01***	*-1.14*	*-1.48*	***1.84***	*-0.24*	***4.96***
Jegadeesh and Titman-Style Momentum Strategy, J=6/K=1, No Skip	2.020	12.97	2.413	-1.884	-0.891	0.777	0.117	3.264
	1.27		*1.54*	*-1.07*	***-2.30***	***2.27***	*0.25*	***4.00***
Jegadeesh and Titman-Style Momentum Strategy, J=6/K=6, No Skip	2.464	11.20	2.601	-1.972	-0.535	0.598	0.083	3.474
	1.79		***1.86***	*-1.32*	*-1.63*	***2.07***	*0.21*	***5.05***
Panel D: Portfolios Chosen from Stocks with Coverage of at Least 15 Analysts								
Jegadeesh and Titman-Style Momentum Strategy, J=6/K=1, Skip 1 month	3.393	14.23	3.761	-1.174	-0.814	0.594	-0.044	3.749
	1.94		***2.10***	*-0.58*	***-1.83***	*1.52*	*-0.08*	***4.02***
Jegadeesh and Titman-Style Momentum Strategy, J=6/K=6, Skip 1 month	2.278	11.24	2.645	-1.757	-0.619	0.214	-0.343	3.344
	1.65		***1.83***	*-1.11*	***-1.78***	*0.70*	*-0.81*	***4.58***
Jegadeesh and Titman-Style Momentum Strategy, J=6/K=1, No Skip	2.006	14.12	2.456	-2.182	-0.955	0.581	0.041	3.523
	1.15		*1.40*	*-1.09*	***-2.17***	*1.50*	*0.08*	***3.81***
Jegadeesh and Titman-Style Momentum Strategy, J=6/K=6, No Skip	2.256	12.07	2.610	-2.153	-0.701	0.327	-0.201	3.618
	1.52		***1.69***	*-1.28*	***-1.90***	*1.00*	*-0.45*	***4.66***

Table 8

Percentage Monthly Returns and Regression Estimates for Industry Price Momentum Portfolios, 1996 to 2001:6

This table shows percentage monthly returns (column 1), standard deviations (column 2), and estimates from time-series regressions of calendar-time portfolios formed using industry price momentum strategies, as discussed in Section I.B. For each of the 59 GICS industries, a monthly return series is calculated based on an equal weighting of all stocks in that industry that month. Industries are then ranked using their geometrically-compound monthly returns for the past *J* months. Portfolios are long all the stocks in the 6 highest ranking industries and short all the stocks in the 6 lowest ranking industries. Industry returns are equally weighted in the long and short portfolios. We create, where *K* denotes number of months the portfolio is held consistent with Jegadeesh and Titman (1993), portfolios for *J=3/K=1* and *J=3/K=3*. Both "skip" and "no skip" portfolios are constructed, where "skip" denotes portfolios for which investors let a month pass between when industries are selected and when stocks are bought and sold for portfolios. Column 3 shows the intercept from the Fama and French 3-factor model. Columns 4-8 show estimates for the 4-factor model, where the 4th factor is the return from recommendation-based Changes Strategy #2. Panel A shows results when stocks can be selected for portfolios regardless of market cap or analyst coverage. Panels B and C show results when stocks are restricted by CRSP market cap decile to $\geq$ 6 and 10 respectively. Panel D shows results when stocks are restricted to analyst coverage $\geq$ 15. T-statistics in **bold** indicate significance at the 10% level.

	Mean Return	Std. Dev.	Intercept from		Coefficient Estimate for 4-Factor Model			
			F&F	4-Factor	Rm - Rf	SMB	HML	Rec. Fac.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Portfolios Chosen from All Stocks								
Industry Price Momentum Strategy, J=3/K=1, Skip 1 month	1.923	11.70	1.725	-1.720	-0.273	1.056	0.615	2.617
	1.33		*1.24*	*-1.07*	*-0.77*	***3.37***	*1.43*	***3.51***
Industry Price Momentum Strategy, J=3/K=3, Skip 1 month	1.410	10.29	1.238	-2.432	-0.238	0.938	0.453	2.788
	1.11		*1.01*	***-1.81***	*-0.81*	***3.60***	*1.26*	***4.49***
Industry Price Momentum Strategy, J=3/K=1, No Skip	2.180	12.55	2.118	-0.996	-0.388	0.740	0.506	2.365
	1.41		*1.35*	*-0.53*	*-0.94*	***2.03***	*1.01*	***2.72***
Industry Price Momentum Strategy, J=3/K=3, No Skip	1.689	10.73	1.472	-1.968	-0.233	0.935	0.587	2.613
	1.28		*1.14*	*-1.34*	*-0.72*	***3.29***	*1.50*	***3.86***
Panel B: Portfolios Chosen from Stocks with Market Capitalization of CRSP Decile 6 or Greater								
Industry Price Momentum Strategy, J=3/K=1, Skip 1 month	1.840	10.36	1.696	-0.843	-0.262	0.906	0.564	1.929
	1.44		*1.37*	*-0.57*	*-0.81*	***3.15***	*1.43*	***2.82***
Industry Price Momentum Strategy, J=3/K=3, Skip 1 month	1.411	9.61	1.192	-2.103	-0.161	0.894	0.477	2.504
	1.19		*1.04*	*-1.65*	*-0.58*	***3.62***	*1.40*	***4.26***
Industry Price Momentum Strategy, J=3/K=1, No Skip	2.648	11.33	2.655	0.538	-0.369	0.569	0.412	1.608
	1.90		***1.86***	*0.31*	*-0.96*	*1.67*	*0.88*	***1.98***
Industry Price Momentum Strategy, J=3/K=3, No Skip	1.712	10.07	1.527	-1.618	-0.233	0.809	0.536	2.389
	1.38		*1.25*	*-1.15*	*-0.75*	***2.97***	*1.43*	***3.68***

Table 8 (continued)

Percentage Monthly Returns and Regression Estimates for Industry Price Momentum Portfolios, 1996 to 2001:6

	Mean Return (1)	Std. Dev. (2)	Intercept from F&F (3)	Intercept from 4-Factor (4)	Coefficient Estimate for 4-Factor Model Rm - Rf (5)	SMB (6)	HML (7)	Rec. Fac. (8)
Panel C: Portfolios Chosen from Stocks with Market Capitalization of CRSP Decile 10								
Industry Price Momentum Strategy, J=3/K=1, Skip 1 month	2.354	11.26	2.334	-0.520	-0.394	0.579	0.439	2.168
	1.70		*1.65*	*-0.31*	*-1.06*	***1.77***	*0.97*	***2.78***
Industry Price Momentum Strategy, J=3/K=3, Skip 1 month	1.789	10.19	1.762	-2.145	-0.371	0.698	0.289	2.968
	1.43		*1.41*	*-1.58*	*-1.24*	***2.64***	*0.79*	***4.72***
Industry Price Momentum Strategy, J=3/K=1, No Skip	3.011	11.91	3.530	1.578	-0.724	0.170	-0.240	1.483
	2.05		***2.31***	*0.83*	***-1.74***	*0.46*	*-0.47*	***1.69***
Industry Price Momentum Strategy, J=3/K=3, No Skip	2.219	10.19	2.325	-0.850	-0.444	0.492	0.166	2.411
	1.77		***1.81***	*-0.57*	*-1.36*	***1.70***	*0.42*	***3.51***
Panel D: Portfolios Chosen from Stocks with Coverage of at Least 15 Analysts								
Industry Price Momentum Strategy, J=3/K=1, Skip 1 month	2.359	12.45	2.202	-1.989	-0.302	0.516	0.457	3.183
	1.54		*1.38*	*-1.09*	*-0.76*	*1.46*	*0.94*	***3.79***
Industry Price Momentum Strategy, J=3/K=3, Skip 1 month	1.854	11.10	1.880	-2.646	-0.397	0.445	0.118	3.438
	1.36		*1.32*	***-1.73***	*-1.18*	*1.50*	*0.29*	***4.86***
Industry Price Momentum Strategy, J=3/K=1, No Skip	2.943	12.06	3.215	-0.001	-0.518	0.323	-0.136	2.443
	1.98		***2.07***	*0.00*	*-1.27*	*0.90*	*-0.27*	***2.85***
Industry Price Momentum Strategy, J=3/K=3, No Skip	2.305	11.13	2.446	-1.538	-0.48211	0.41068	0.04474	3.02632
	1.68		***1.72***	*-0.96*	*-1.37*	*1.32*	*0.10*	***4.10***

Table 9

Further Examination of the Link Between Analyst Information and Price Momentum

This table shows results of chi-square tests of whether recommendations impact the probability that stocks are selected for Jegadeesh and Titman-style price momentum portfolios (top half of table) and whether analysts are more likely to make recommendation changes for stocks that meet the cutoffs for these momentum portfolios (bottom half of table). Price momentum portfolios have one-month holding periods and are long stocks ranking in the highest 10% based on past 6-month returns and short stocks ranking in the lowest 10% based past 6-month returns. In the top half of the table, columns 1, 3, and 2, respectively, show the probability that a stock is short, long, or not in the price momentum portfolio conditional on that stock's being net upgraded or net downgraded in the most recent month used to calculate 6-month compound returns used as the criteria for momentum portfolio stock selection. In the bottom half of the table, columns 1, 2, and 3, respectively, show the probability that a stock is net upgraded, has zero net recomendation changes, or is net downgraded conditional on that stock's meeting the criteria for momentum portfolio stock selection based on past 6-month returns. The p-values (<.0001) indicate that we reject the null hypothesis of randomness in every panel.

	Probability (%) that stock is: Short in Mom. Port. (1)	Not in Mom. Port. (2)	Long in Mom. Port. (3)	***p*-Value from Chi-Square Test (4)**
Panel A: Portfolios Chosen from All Stocks				
Conditional on stock net downgraded	14.8	77.1	8.1	*< .0001*
Conditional on stock net upgraded	4.0	82.6	13.4	
Unconditionally	***9.5***	***81.1***	***9.5***	
Panel B: Portfolios Chosen from Stocks with Market Capitalization of CRSP Decile 6 or Greater				
Conditional on stock net downgraded	17.3	74.5	8.2	*< .0001*
Conditional on stock net upgraded	5.6	81.4	13.0	
Unconditionally	***9.5***	***81.0***	***9.5***	
Panel C: Portfolios Chosen from Stocks with Market Capitalization of CRSP Decile 10				
Conditional on stock net downgraded	16.4	75.1	8.5	*< .0001*
Conditional on stock net upgraded	7.4	80.0	12.6	
Unconditionally	***9.7***	***80.6***	***9.7***	
Panel D: Portfolios Chosen from Stocks with Coverage of at Least 15 Analysts				
Conditional on stock net downgraded	17.1	74.4	8.5	*< .0001*
Conditional on stock net upgraded	6.9	80.4	12.7	
Unconditionally	***9.9***	***80.3***	***9.9***	

	Probability (%) that stock is: Net Downgraded (1)	Has Net 0 Rec. Δ's (2)	Net Upgraded (3)	***p*-Value from Chi-Square Test (4)**
Panel A: Portfolios Chosen from All Stocks				
Conditional that stock is short in momentum port.	8.2	86.7	5.0	*< .0001*
Conditional that stock is long in momentum port.	6.3	79.5	14.1	
Unconditionally	***6.9***	***82.6***	***10.6***	
Panel B: Portfolios Chosen from Stocks with Market Capitalization of CRSP Decile 6 or Greater				
Conditional that stock is short in momentum port.	17.2	70.5	12.3	*< .0001*
Conditional that stock is long in momentum port.	10.7	66.7	22.6	
Unconditionally	***11.5***	***70.9***	***17.6***	
Panel C: Portfolios Chosen from Stocks with Market Capitalization of CRSP Decile 10				
Conditional that stock is short in momentum port.	26.2	49.6	24.2	*< .0001*
Conditional that stock is long in momentum port.	17.3	51.4	31.3	
Unconditionally	***18.5***	***55.1***	***26.4***	
Panel D: Portfolios Chosen from Stocks with Coverage of at Least 15 Analysts				
Conditional that stock is short in momentum port.	34.0	40.8	25.3	*< .0001*
Conditional that stock is long in momentum port.	20.6	42.4	36.9	
Unconditionally	***22.6***	***47.3***	***30.1***	

Table 10
Contribution of Recommended Stocks to Price Momentum Returns

This table shows the contribution of the returns from recommended stocks to price momentum portfolio returns. Mean returns are calculated separately for stocks in the long and short sides of price momentum portfolios conditional on whether these stocks were net upgraded, downgraded, or neither. Price momentum portfolios have one-month holding periods and are long stocks ranking in the highest 10% based on past 6-month returns and short stocks ranking in the lowest 10% based past 6-month returns. Portfolios can be chosen from all stocks regardless of market capitalization or analyst coverage and have a one-month skip between stock selection and trade execution. Stock's upgrade, downgrade, or unchanged status is for the "skip" month. Column 1 shows net upgraded, downgraded, and unchanged stocks as a percentage of the long side ("Best 10%") and short side ("Worst 10%") of the price momentum portfolios. Column 2 shows the mean return for stocks in each category in the calendar month following the recommendation changes. Columns 3 shows the contribution of this return as an absolute one-month percentage return toward the momentum portfolio strategy's mean one-month return ("Best 10% - Worst 10%"). Column 4 shows this return's percentage contribution to the momentum portfolio strategy's mean one-month return.

		Percetage of Stocks Used on Long or Short Side of Portfolio	Mean Return (%)	Contribution to Price Momentum Returns: As % Return	Contribution to Price Momentum Returns: As % of Total Return
		(1)	(2)	(3)	(4)
Best 10%:	Upgraded	*14%*	3.826	*0.540*	34.0%
	Net Δ's = 0	*80%*	2.401	*1.910*	
	Downgraded	*6%*	2.013	*0.128*	
		100%			
Worst 10%:	Upgraded	*5%*	-0.135	*0.007*	
	Net Δ's = 0	*87%*	1.199	*-1.040*	
	Downgraded	*8%*	-0.555	*0.046*	2.9%
		100%			
Best 10% - Worst 10%				*1.590*	

Appendix 1
Industry Group Descriptive Statistics

This appendix shows descriptive statistics for the 59 S&P/MSCI GICS industries. Columns 1and 2 list the code number and name assigned by the S&P/MSCI Global Industry Classification Standard for each industry. Column 3 shows that the number of companies in the industry. Column 4 shows the number of companies in the industry with a CRSP size decile of 6 or greater. Column 5 shows this number as the percentage of all companies in the industry. Column 6 shows the number of companies that have the coverage of at least one analyst during the January 1996 through June 2001 timeframe. Column 7 shows this number as the percentage of all companies in the industry. Column 8 indicates the average number of analysts per covered company within the industry. Column 9 shows the average number of recommendations per covered company during January 1996 through June 2001.

	Industry Code (1)	IndustryName (2)	Number of Companies (3)	Number of of Companies with Decile of 6 or more (4)	% of Total (5)	Number of of Companies Covered by Analysts (6)	% of Total (7)	Average Number of Analysts per Covered Company (8)	Average Number of Recommendations per Covered Company (9)
1	101010	Energy Equipment & Services	124	79	63.7%	99	79.8%	7.4	32.2
2	101020	Oil & Gas	363	176	48.5%	213	58.7%	6.8	29.8
3	151010	Chemicals	190	95	50.0%	125	65.8%	5.0	22.7
4	151020	Construction Materials	37	19	51.4%	24	64.9%	3.5	14.6
5	151030	Containers & Packaging	72	34	47.2%	47	65.3%	4.0	16.6
6	151040	Metals & Mining	232	80	34.5%	133	57.3%	5.2	31.5
7	151050	Paper & Forest Products	61	35	57.4%	40	65.6%	6.1	28.1
8	201010	Aerospace & Defense	110	54	49.1%	75	68.2%	4.4	17.9
9	201020	Building Products	77	31	40.3%	42	54.5%	3.4	17.3
10	201030	Construction & Engineering	89	29	32.6%	43	48.3%	3.7	14.3
11	201040	Electrical Equipment	142	65	45.8%	94	66.2%	3.4	13.6
12	201050	Industrial Conglomerates	17	8	47.1%	15	88.2%	4.8	17.0
13	201060	Machinery	266	114	42.9%	164	61.7%	3.5	15.6
14	201070	Trading Companies & Distrib	18	8	44.4%	13	72.2%	3.8	19.6
15	202010	Commercial Svcs & Supplies	655	229	35.0%	344	52.5%	3.9	15.9
16	203010	Air Freight & Couriers	35	19	54.3%	25	71.4%	7.6	32.3
17	203020	Airlines	45	21	46.7%	37	82.2%	5.7	27.7
18	203030	Marine	17	6	35.3%	10	58.8%	2.5	6.3
19	203040	Road & Rail	106	48	45.3%	73	68.9%	4.0	21.6
20	203050	Trans Infrastructure	9	1	11.1%	2	22.2%	1.5	8.0
21	251010	Auto Components	124	48	38.7%	82	66.1%	4.6	17.9
22	251020	Automobiles	33	15	45.5%	23	69.7%	6.1	26.6
23	252010	Household Durables	224	84	37.5%	145	64.7%	3.5	15.7
24	252020	Leisure Equipment & Products	122	26	21.3%	70	57.4%	2.8	13.3
25	252030	Textiles & Apparel	191	47	24.6%	118	61.8%	3.5	15.8
26	253010	Hotels Restaurants & Leisure	362	127	35.1%	214	59.1%	4.4	19.8

Appendix 1 (continued)

	Industry Code (1)	IndustryName (2)	Number of Companies (3)	Number of of Companies with Decile of 6 or more (4)	% of Total (5)	Number of of Companies Covered by Analysts (6)	% of Total (7)	Average Number of Analysts per Covered Company (8)	Average Number of Recommendations per Covered Company (9)
27	254010	Media	440	200	45.5%	264	60.0%	4.7	17.5
28	255010	Distributors	128	18	14.1%	42	32.8%	2.0	9.6
29	255020	Internet & Catalog Retail	105	41	39.0%	78	74.3%	4.0	16.3
30	255030	Multiline Retail	67	36	53.7%	49	73.1%	8.4	32.1
31	255040	Specialty Retail	296	107	36.1%	197	66.6%	5.6	27.4
32	301010	Food & Drug Retailing	117	59	50.4%	75	64.1%	4.7	18.3
33	302010	Beverages	50	17	34.0%	38	76.0%	5.9	28.6
34	302020	Food Products	182	77	42.3%	116	63.7%	3.9	21.2
35	302030	Tobacco	19	11	57.9%	14	73.7%	5.4	19.8
36	303010	Household Products	20	10	50.0%	14	70.0%	7.4	32.4
37	303020	Personal Products	63	13	20.6%	34	54.0%	3.2	13.9
38	351010	Health Care Equipment & Supp	445	156	35.1%	299	67.2%	3.7	14.5
39	351020	Health Care Providers & Svcs	402	151	37.6%	257	63.9%	5.0	23.6
40	352010	Biotechnology	323	178	55.1%	239	74.0%	4.1	12.5
41	352020	Pharmaceuticals	199	100	50.3%	146	73.4%	5.7	21.6
42	401010	Banks	1,309	488	37.3%	774	59.1%	3.7	12.6
43	402010	Diversified Financials	435	189	43.4%	204	46.9%	4.9	19.0
44	403010	Insurance	321	206	64.2%	220	68.5%	6.0	19.3
45	404010	Real Estate	390	202	51.8%	215	55.1%	5.1	18.8
46	451010	Internet Software & Services	483	178	36.9%	374	77.4%	5.1	15.7
47	451020	IT Consulting & Services	150	51	34.0%	112	74.7%	4.1	21.9
48	451030	Software	642	256	39.9%	468	72.9%	4.3	18.3
49	452010	Communications Equipment	319	164	51.4%	252	79.0%	5.8	25.2
50	452020	Computers & Peripherals	238	88	37.0%	158	66.4%	4.0	22.4
51	452030	Electronic Equip & Instru	322	113	35.1%	204	63.4%	4.1	18.4
52	452040	Office Electronics	20	8	40.0%	13	65.0%	4.5	17.2
53	452050	Semiconductor Equip & Prods	256	157	61.3%	204	79.7%	5.9	30.3
54	501010	Diversified Telecomm Svcs	217	102	47.0%	158	72.8%	6.3	26.6
55	501020	Wireless Telecomm Svcs	96	56	58.3%	70	72.9%	6.1	22.2
56	551010	Electric Utilities	117	90	76.9%	101	86.3%	8.4	28.3
57	551020	Gas Utilities	78	58	74.4%	62	79.5%	6.0	17.0
58	551030	Multi-Utilities	37	32	86.5%	27	73.0%	10.7	30.9
59	551040	Water Utilities	21	14	66.7%	18	85.7%	3.4	9.8
		Total	12,028	5,124	42.6%	7,766	64.6%		

Appendix 2

Definitions of Returns from Recommendation Portfolios

Consensus Level Strategy #1

Let $R_{A,pt}$ denote the month t return of the Consensus Level Strategy #1 portfolio, which is formed using consensus level information available as of the end of month t - 1. Then:

$$R_{A,pt} = \frac{1}{N_t} \sum_{k=1}^{N_t} \left(\frac{1}{n_{kt,B}} \sum_{i=1}^{n_{kt,B}} R_{ikt} - \frac{1}{n_{kt,W}} \sum_{j=1}^{n_{kt,W}} R_{jkt} \right) \tag{1}$$

where

R_{ikt} = the return for month t on the stock of company i, which has the best consensus level in industry k as of the end of month t - 1.

R_{jkt} = the return for month t on the stock of company j, which has the worst consensus level in industry k as of the end of month t - 1.

$n_{kt,B}$ = the number of companies that have the best consensus level in industry k at the end of month t - 1.

$n_{kt,W}$ = the number of companies that have the worst consensus level in industry k at the end of month t - 1.

N_t = the number of industries for which there exist at least 2 companies with different consensus levels at the end of month t - 1.

Consensus Level Strategy #2

Let $R_{B,pt}$ denote the month t return of the Consensus Level Strategy #2 portfolio. Then:

$$R_{B,pt} = \frac{1}{n_{t,B}} \sum_{i=1}^{n_{t,B}} R_{it} - \frac{1}{n_{t,W}} \sum_{j=1}^{n_{t,W}} R_{jt} \tag{2}$$

where

R_{it} = the return for month t on the stock of company i, which has a consensus level ≤ 1.5 at the end of month t - 1.

R_{jt} = the return for month t on the stock of company j, which has a consensus level > 3.0 at the end of month t - 1.

$n_{t,B}$ = the number of companies that have a consensus level ≤ 1.5 at the end of month t - 1.

$n_{t,W}$ = the number of companies that have a consensus level > 3.0 at the end of month t - 1.

Unlike Equation (1), in Equation (2), stocks are equally weighted without regard for industry.

Changes Strategy #1

The return for the Changes Strategy #1 portfolio takes the form of Equation (1), except:

R_{ikt} = the return for month t on the stock of company i, which has the most positive AgChange in industry k for month t - 1.

R_{jkt} = the return for month t on the stock of company j, which has the most negative AgChange in industry k for month t - 1.

$n_{kt,B}$ = the number of companies that have the most positive AgChange in industry k for month t - 1.

$n_{kt,W}$ = the number of companies that have the most negative AgChange in industry k for month t - 1.

N_t = the number of industries for which there exist at least one company with a positive AgChange and at least one company with a negative AgChange for month t - 1.

Changes Strategy #2

The return for the Changes Strategy #2 portfolio each month is calculated similarly,

except:

R_{ikt} = the return for month t on the stock of company i, which has a positive AgChange in industry k for month t - 1.

R_{jkt} = the return for month t on the stock of company j, which has a negative AgChange in industry k for month t - 1.

$n_{kt,B}$ = the number of companies in industry k that have a positive AgChange for month t - 1.

$n_{kt,W}$ = the number of companies in industry k that have a negative AgChange for month t - 1.