Choosing Winners from Losers: Identifying Value Based on Analyst Consensus Recommendation Changes*

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Abstract

Based on empirical evidence, price momentum strategies have demonstrated power to predict stock returns. The change in sell-side consensus analyst recommendations has also been identified as a robust return predictor. Our study is unique in that we simultaneously introduce both this change in consensus recommendations, along with historical price performance, as independent variables. We have found that the portfolio of stocks which underperformed ("losers") yet were upgraded, during the trailing 1-month period, generate significant excess returns in various scenarios. In the base scenario, this **LOW-UP** portfolio displayed an excess monthly return of 1.86%. This would imply that contrary to prior research, not all losers are the same.

Sell-side analyst recommendations are a ubiquitous feature in US equity markets. CNBC and other financial news feeds continually bombard market participants with the investment viewpoints of the large investment banks. In addition to news channels, retail brokers distribute in-house recommendations to their clients. Finally, institutional portfolio managers and buy-side analysts regularly consult with their sell side counterparts.

Given the broad dissemination of analyst picks, it is rational to ask whether these recommendations add value. Jegadeesh, Kim, Krische, and Lee (JKKL, 2004) examine the predictive power of analyst recommendations. JKKL show that the ***level*** of analyst recommendation only adds value when coupled with favorable quantitative characteristics; in fact, highly positive consensus recommendations, when associated with unfavorable quantitative recommendations, lead to subsequent underperformance. Interestingly, however, JKKL show that ***changes*** in consensus recommendations are a robust return predictor.

In addition to the burgeoning literature focused on analyst recommendations, academics have spent a great deal of effort examining whether past stock returns influence future returns. DeBondt and Thaler (1985) sparked considerable debate by demonstrating that selling past winners and buying past losers generates abnormal returns over 3 to 5 year holding periods. In this study, past winners and losers were determined

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by looking at firm share performance over the preceding 3 to 5 years. In this long dated study, the authors contend that stock prices overreact to information leading to significant reversion to the mean. More recently, Jegadeesh (1989) found significant evidence of negative serial correlation in monthly stock returns; in other words, stocks that go up one month tend to fall the next one. Over longer time periods (three months to two years), stocks exhibit significant positive serial correlation. Building on this work, Jegadeesh and Titman (1993) find that "strategies which buy stocks that have performed well in the past and sell stocks that have performed poorly in the past generate significant positive returns over 3 to 12 month holding periods".

Our analysis rests at the nexus of these two research fields. Specifically, we examine whether considering prior stock performance enhances the predictive power of changes in consensus analyst recommendations. In this paper, we examine the performance of portfolios formed on the basis of relative price momentum and relative consensus ratings changes. Our methodology builds on the work of Asness (1997) who probed the interaction between value and momentum strategies. We find that buying a portfolio of stocks (**LOW-UP**) which exhibited relative weak price momentum over the preceding one month, but had the most positive relative ratings changes, yields significant positive excess returns over the following month. Specifically, the **LOW-UP** portfolio exhibited monthly abnormal returns of 1.86%. Significance is maintained even when controlling for risk (market risk premia, size premia, and book value premia are all considered). Finally, in order to ensure the practicality of our methodology, we examined the performance of portfolios constructed using a two day lag period between the release of I/B/E/S ratings snapshots and portfolio changes. The use of a lag period did not degrade abnormal returns in the **LOW-UP** portfolio. Returns of the other three examined portfolios (**HIGH-UP, HIGH-DOWN, LOW-DOWN**) were not significantly different from market returns. The following table highlights the composition of the four examined portfolios.

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Table 1: Portfolio Composition

Portfolio	Description
HIGH-UP	This portfolio contains stocks that were both among the *best* relative performers over the prior month and had the *most positive* analyst consensus ratings changes.
HIGH-DOWN	This portfolio contains stocks that were among the *best* relative performers over the prior month, but had the *most negative* consensus ratings changes.
LOW-UP	This portfolio contains stocks that were among the *worst* relative performers over the prior month, but had the *most positive* consensus ratings changes.
LOW-DOWN	This portfolio contains stocks that were both among the *worst* relative performers over the prior month and had the *most negative* analyst consensus ratings changes.

The significant excess returns generated by the **LOW-UP** portfolio beg comparison to previous research in the field. First, it would be incorrect to assign the performance of the **LOW-UP** portfolio to the negative serial correlation seen by Jegadeesh (1989); while the **LOW-UP** portfolio generated excess returns, the **LOW-DOWN** portfolio (which also contained poor relative performers) did not show abnormal returns. In addition, the **LOW-UP** portfolio is not a generic "value" strategy. Although Lakonishok, Shleifer, and Vishny (1994) find that a number of different value strategies have outperformed glamour strategies over long time horizons, the stocks making up the **LOW-UP** performance are not necessarily value stocks. Given that serial correlation and value factors cannot explain the performance of the **LOW-UP** portfolio, one should consider alternative sources of portfolio alpha. The following section explores the rationale, based on work in the field of behavioral finance, for why upgrades following a period of negative performance constitute such a powerful buy signal.

Behavioral Finance

Barberis and Thaler (2002) postulate that investor psychology is a powerful driver of purchase and sale decisions. Specifically, the authors cite a number of biases, perceptions, and beliefs which can cause market action to deviate from standard efficient market predictions. These biases can serve as an interesting intellectual framework to explain corner portfolio performance.

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Self-attribution bias and hindsight bias both provide insight into the performance of the **HIGH-UP** and **LOW-DOWN** portfolios. Self-attribution bias refers to an individual's tendency to place more weight on data that supports their existing beliefs while simultaneously ignoring data that calls their investment thesis into question. Additionally, self-attribution bias refers to an investor's tendency to attribute successes to the possession of superior skills; on the flip side, investors tend to view their failures as the result of unforeseen exogenous events (rather than as a result of poor diligence). If an investor is already long a stock, and an analyst upgrades it, she is not very likely to add to her position. In this situation, the investor "knows" that the stock is undervalued; the positive recommendation from an analyst just confirms her existing belief. Applied directly to our situation, the self-attribution bias clearly limits the potential for excess returns in the **HIGH-UP** portfolio.

Self attribution bias also has a profound impact on the likely performance of the **LOW-DOWN** portfolio. If an analyst issues a sell recommendation on a stock that has already declined, investors will perceive the recommendation as a confirmatory signal. In addition, short sale constraints may also limit negative price action following a downgrade (these constraints are discussed below). In addition, JKKL (2004) find that sell side analysts are "late" in downgrading stocks; often, downgrades occur only after quantitative investment signals have turned decidedly negative. Therefore investors are likely to discount downgrades that are preceded by periods of underperformance. Finally, hindsight bias contributes to the results of both the **LOW-DOWN** and **HIGH-UP** portfolios (Hindsight bias refers to an individual's tendency to believe that they correctly predicted an event would happen [such as an analyst issuing a buy recommendation] after it has already happened).

Having examined behavioral biases affecting two of the portfolios, we need to address why the **LOW-UP** portfolio exhibits such strong excess returns. We believe that contrarian analyst recommendations are likely to contain more information than a "me-too" recommendation. This informational divergence is discussed in greater detail in the final section of this paper. Despite the existence of countervailing recommendations in the **HIGH-DOWN** portfolio, we do not observe significant underperformance. We attribute this lack of poor relative performance to short sale constraints.

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Short sale constraints help explain why there is no significant underperformance of the **HIGH-DOWN** portfolio (the mirror to the **LOW-UP** portfolio). The average retail investor is much more likely to purchase a stock then to short a stock; investor portfolios are filled with long positions, not short ones. The lack of retail short interest can be attributed to multiple factors. Some investors are not sure of the actual mechanics of short sales while other investors face psychological constraints for short sales (psychological constraints range from not understanding the sell-high buy-low order of short sales to having moral issues with shorting a stock). While retail investors shy away from short sales, one could argue that institutional investors would pick up any slack. In fact, research shows that most large cap stocks are both cheap and easy to borrow. Two factors, however, constrain institutional shorting activity. First, institutional biases lessen the likelihood of shorting. Almazan et al. (2002) found that thirty percent of mutual funds are allowed to sell short, but only two percent take advantage of this ability. Second, we believe that due to superior access to information and market resources, institutional investors are less likely to be swayed by analyst recommendations than are retail investors.

I. Portfolio Construction and Single Factor Results

Our initial dataset consists of I/B/E/S consensus analyst recommendations on the stocks in the Dow Jones Industrial Average. Since the Dow constituents change over time, we fixed our analysis based on the most recent Dow composition (April 2004). The examined I/B/E/S dataset contains summary consensus recommendation information from December 1992 to February 2003. I/B/E/S collects sell-side recommendations from contributing firms, standardizes the ratings on a numerical scale (1 for strong buy, 3 for hold, and 5 for strong sell), and averages these ratings across firms. These consensus ratings are available to paying subscribers on a real time basis. In addition to real-time data, I/B/E/S records a snapshot of current consensus recommendations in a history file; this snapshot is generally produced on the third Thursday of every month. After this date, the historical dataset is available via CD or download. We used this date as the baseline for our analysis.

At the date of the I/B/E/S snapshot, we ranked the 30 stocks in the Dow by their total returns since the previous data release (i.e. stocks are ranked by one month historical

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performance). In order to capture stock performance, we used holding period return data from the CRSP daily returns file. After ranking the stocks by performance, they were placed into buckets categorizing their relative momentum. The top ten performing stocks were classified in the **HIGH** bucket (top 1/3) while the bottom ten performing stocks were placed in the **LOW** bucket (bottom 1/3).

In addition to ranking the Dow 30 by relative performance, we ranked each of the examined stocks by change in consensus analyst recommendation. The ten stocks with the strongest ratings movements were placed in the **UP** bucket (top 1/3); the ten stocks with the weakest ratings movements were placed in the **DOWN** bucket (bottom 1/3). Given that certain discrete movements in consensus analyst recommendation were quite common, ties were included in each of the portfolios (i.e. if four stocks all tied for the 10^{th} strongest ratings movement, the **UP** bucket would contain 13 stocks for that period). Across the entire sample, approximately 40% of months exhibited **UP** or **DOWN** buckets with greater than 10 stocks.

In order to study the effects of prior stock performance on the power of analyst recommendations, we formed four "corner" portfolios from the buckets. Specifically, stocks that were in both the **HIGH** and **UP** buckets were included in the **HIGH-UP** portfolio for that month on an equal weighted basis. An identical methodology was followed to form the other three portfolios (**HIGH-DOWN**, **LOW-UP**, **LOW-DOWN**). Given the outlined methodology, it should be clear that the number of stocks in each portfolio varied. Additionally, in certain cases, a portfolio could contain no stocks in a given month; in these cases, portfolio returns were assumed to equal market returns. While there was significant variation, the portfolios contained, on average 3.2 stocks per month. Finally, the examined portfolios contained no stocks about 2.7% of the time.

After formation, we tracked the performance of these corner portfolios over the following month. Specifically, we regressed the portfolio excess returns against the market's excess returns over the entire dataset. Daily market excess returns were obtained from the daily Fama/French Factors data file. The actual regression equation follows:

$$r(portfolio)_t - r_m = \alpha + \beta(r_m - r_f)_t + \varepsilon$$

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When conducting portfolio analysis, one must ensure that the strategies being considered are actually implementable. Therefore, in addition, to the base case scenario where the portfolio was formed the day after the historical snapshot was taken, we formed a 2 day lag portfolio. Importantly, the release of the consensus ratings really does not constitute new public information (this I/B/E/S consensus recommendation information is available to real time subscribers); however, we wanted to ensure that idiosyncratic timing effects were not driving our results. The utilized lag should be sufficient to eliminate any "look-ahead" bias.

Table 2: Univariate Monthly Returns

As explained above, the portfolios are formed using two approaches: No Lag and 2-Day Lag. The top sub-row indicates the coefficient from the regression. The second row in parentheses displays the implied t-statistic. For reference, α can be construed as the implied monthly excess return; β indicates the portfolios covariance with the market.

	High-Up	High-Down	Low-Up	Low-Down
No Lag				
α	0.16%	-0.21%	1.86%	-0.02%
	(0.413)	(-0.465)	(3.670)	(-0.043)
β	0.82	0.76	0.67	0.99
	(10.141)	(8.077)	(6.314)	(13.075)
2-Day Lag				
α	0.20%	-0.36%	1.66%	0.16%
	(0.503)	(-0.771)	(3.148)	(0.312)
β	0.92	0.76	0.74	0.98
	(11.120)	(7.736)	(6.691)	(8.832)

As one can see, the **LOW-UP** portfolio generated significant excess returns in both the no lag and 2-day lag scenarios. Specifically, this portfolio exhibited a monthly alpha of 1.86% and 1.66% respectively. In addition, the t-statistics of 3.670 and 3.148 were both statistically significant (p values of 0.000383 and 0.002129 respectively). It is also apparent that the other three portfolios did not display statistical significance. The following table presents the annualized excess returns for the four strategies.

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Chart 1: Univariate Annualized Excess Returns

This graphic shows the chasm in excess returns between the four strategies. Specifically, one can see the void between the High-Up and Low-Up portfolios. Although both groups of stocks had strong relative ratings changes, only the Low-Up portfolio exhibited strong outperformance.

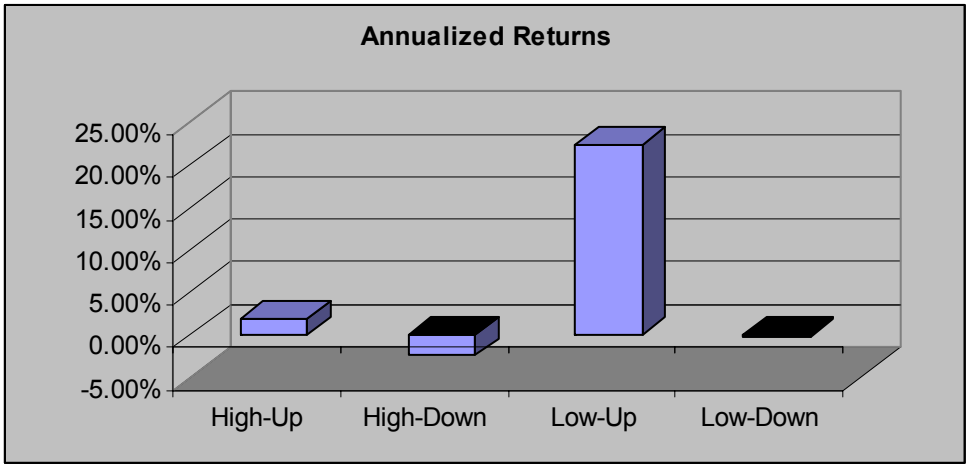
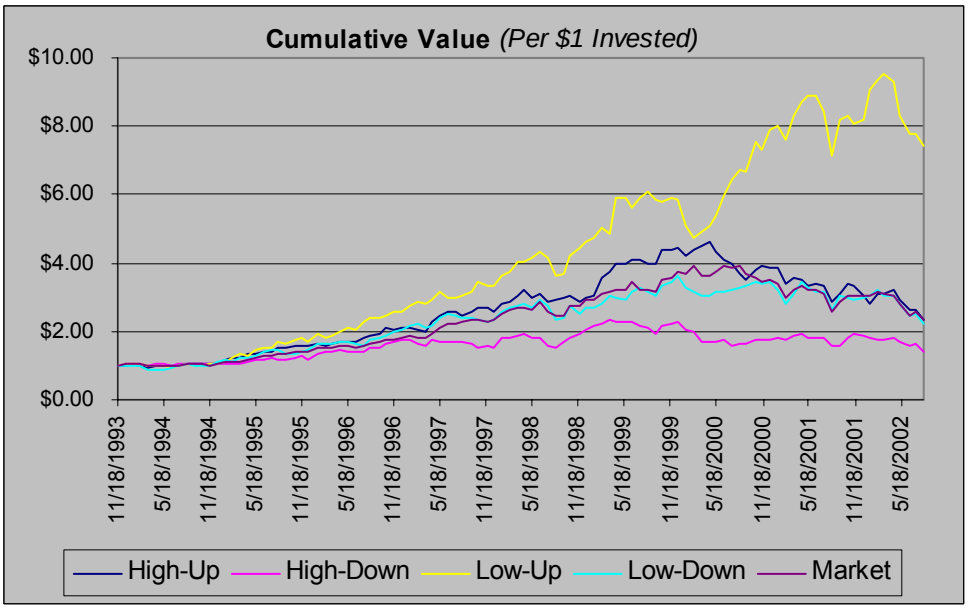


Chart 2: Cumulative Portfolio Returns

This chart lays out the cumulative value of a $1 invested in each of the four strategies outlined above (High-Up, High-Down, Low-Up, Low-Down). For reference, the cumulative value of $1 invested in the market is included as well. One can again see that the Low-Up portfolio is a consistent outperformer. Interestingly, the Low-Up portfolio performed worst in the strong bull market of 1999, but rebounded strongly during the following bear market. This anecdotally suggests that the Low-Up strategy may be a type of "value strategy".



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II. Multiple Factor Model Results

Although univariate analysis against market returns shows strong results for the **LOW-UP** portfolio, we wanted to ensure that other risk factors were not driving excess portfolio returns. Fama and French (1992) find that most variations in stock market returns can be explained by three factors: market returns, book-to-market ratio, and firm size. Therefore, to incorporate these sources of risk in our excess return calculations we performed the following regression:

$$r(portfolio)_t - r_m = \alpha + \beta_1 (r_m - r_f)_t + \beta_2 (SMB)_t + \beta_3 (HML)_t + \varepsilon$$

This regression is the typical Fama/French risk model where r_m-r_f constitutes the market return factor, SMB (small minus big) is the size factor, and HML (high minus low) is the book value factor. The results from this regression are presented below:

Table 3: Multivariate Monthly Returns

The portfolios (High-Up, High-Down, Low-Up, and Low-Down) are formed based on the same criteria in the preceding table.

SMB & HML	High-Up	High-Down	Low-Up	Low-Down
α	-0.13% (-0.167)	1.03% (1.108)	1.68% (1.647)	0.60% (0.805)
β	1.00 (10.358)	0.74 (6.389)	0.92 (7.294)	1.08 (11.650)
SMB	0.01 (0.128)	-0.12 (-1.502)	-0.07 (-0.764)	-0.07 (-1.106)
HML	0.40 (3.188)	-0.02 (-0.108)	0.59 (3.478)	0.23 (1.888)

One can see that the addition of multiple risk factors dampened the alpha of the **LOW-UP** portfolio by 10%. In addition, one can see that the HML t-statistic is quite significant. In fact, the loss of alpha in the **LOW-UP** portfolio can be attributed to the addition of the HML factor. In contrast to HML, the SMB t-statistics were relatively insignificant across the board. This lack of significance is partially due to the fact that all the companies in this analysis are large-cap stocks (i.e. they would all be classified as "big" companies). Accordingly, we opted to drop the SMB variable from our regression. The modified regression results are presented below:

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Table 4: Multivariate Monthly Returns (Excluding SMB)

The removal of the SMB factor clearly highlights the effect of the HML factor. In particular, the HML factor is clearly significant for the Low-Up portfolio. The significance of this factor seems to indicate that a portion of Low-Up's excess returns are driven by valuation. Even when considering market and book value factors, the Low-Up portfolio retains a 12% annualized excess return. The p-value of the Low-Up alpha coefficient is 4.4%.

HML Only	High-Up	High-Down	Low-Up	Low-Down
α	-0.04% (-0.115)	-0.19% (-0.407)	1.00% (2.034)	-0.12% (-0.345)
β	1.00 (10.408)	0.74 (6.392)	0.92 (7.332)	1.09 (11.679)
HML	0.40 (3.223)	-0.04 (-0.241)	0.57 (3.420)	0.22 (1.805)

Given the strong excess returns generated by the **LOW-UP** strategy, we wanted to develop a more thorough understanding in the risks inherent in the various portfolios. Specifically, we attempted to determine if the **LOW-UP** portfolio was inherently more volatile than its peers or the market. Additionally, we assessed whether the strong performance of the **LOW-UP** strategy is driven by a few outlier months. This entailed calculating the standard deviation, maximum, and average monthly returns for each of the four portfolios (in addition, we included the same summary statistics for French's market returns). To examine the effect of outliers, we then removed the top ten monthly returns for each portfolio (and the market) and tracked the corresponding results.

Table 5: Effect of Top 10 Largest Returns on Monthly Portfolio Performance

For reference, the standard deviation each portfolio, as well as its largest monthly return, is included. Interestingly, the minimum returns are similar across all examined portfolios.

	ALL MONTHS				
	High-Down	Low-Down	High-Up	Low-Up	Market
S.D.	5.82%	6.02%	5.46%	6.12%	4.80%
Max	16.83%	15.12%	16.50%	21.36%	12.47%
Min	-13.74%	-16.83%	-15.02%	-15.29%	-16.80%
Ave	0.50%	0.94%	0.97%	2.16%	0.77%

	EXCLUDING TOP 10 MONTHS				
	High-Down	Low-Down	High-Up	Low-Up	Market
S.D.	4.69%	5.28%	4.70%	5.08%	4.22%
Max	6.53%	8.91%	9.08%	10.83%	6.14%
Min	-13.74%	-16.83%	-15.02%	-15.29%	-16.80%
Ave	-0.65%	-0.11%	0.05%	0.98%	-0.06%
Δ in Ave. Return	**-1.15%**	**-1.06%**	**-0.92%**	**-1.17%**	**-0.83%**

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From the above table, we see that, on average, the overall portfolios' monthly return fell by 1.08% when the top ten monthly returns were removed. Specifically, the **LOW-UP** portfolio fell by a reasonable 1.17%; even after this adjustment, the **LOW-UP** portfolio was still the best performer among the five portfolios. The market return profile, in comparison, fell by a more modest 0.83%. This slightly smaller decline is not unexpected; the market's diversification should buffer the extremes of the return distribution. From a volatility perspective, the **LOW-UP** portfolio was the most volatile (with a monthly standard deviation of 6.12%). After removing the top ten months, however, the **LOW-UP** standard deviation of 5.08% is surpassed by the **LOW-DOWN** portfolio. In summary, we find that the drop in monthly returns, as well as the overall volatility, of the **LOW-UP** portfolio to be within reasonable limits. We were therefore comfortable that outliers and excess volatility were not driving excess returns.

III. Implications & Constraints

In this paper, we analyzed the performance of portfolios formed on the basis of relative price momentum and relative consensus ratings changes in the 30 stocks of Dow Industrial Average. In particular, we examined whether considering prior stock performance improves the predictive power of changes in consensus analyst recommendations. As the following table summarizes, it is clear that a portfolio formed from past losers, who also experienced positive ratings momentum, generates significant excess returns.

Table 6: Summary of Portfolio Excess Return Levels

	High Up	High Down	Low Up	Low Down
Univariate (No Lag)	0.16%	-0.21%	1.86%	-0.02%
Univariate (2 Day Lag)	0.20%	-0.36%	1.66%	0.16%
Multivariate (SMB & HML)	-0.13%	1.03%	1.68%	0.60%
Multivariate (HML Only)	-0.04%	-0.19%	1.00%	-0.12%

Clearly, the **LOW-UP** portfolio's robust performance, when coupled with the aforementioned statistically significant t-statistics, warrants further investigation and explanation. Even after controlling for risk (market risk premia, book value premia, and size premia) salient significance is sustained.

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As mentioned in the introduction, the **LOW-UP** results, in many ways, run contrary to Jegadeesh's return reversal (1989). Specifically, it would be incorrect to ascribe the performance of the **LOW-UP** portfolio to the negative serial correlation seen by Jegadeesh (1989); while the **LOW-UP** portfolio generated excess returns, the **LOW-DOWN** portfolio did not show abnormal returns versus the market. In addition, we found that not all "upgraded" stocks generate alpha. Specifically, while the **LOW-UP** portfolio significantly outperformed risk adjusted expectations, the **HIGH-UP** portfolio did not.

While we spend time discussing the behavioral finance explanations for portfolio performance in the opening section of the paper, we believe that a major driver of **LOW-UP** performance stems from superior information content. Specifically, upgrades which follow periods of strong price performance (the **HIGH-UP** portfolio) may represent "me-too" recommendations. These recommendations may reflect prior market action, recent positive news flow, and improved fundamentals, but offer little information about future return potential. In contrast, upgrades following periods of price weakness represent a departure from "consensus" thought. Anecdotally, these upgrades tend to represent a real fundamental call. Specifically, the analyst may argue persuasively that current price performance is not indicative of the company's value. These arguments may contain new information that the market has not fully incorporated into prices. As this information becomes known, price appreciation follows.

While we firmly believe that our analysis shows that a portfolio consisting of stocks with positive ratings momentum and negative price momentum generates excess returns, our data set and analysis was limited by a number of factors. These limitations could form the basis of continuing research aimed at solidifying the findings presented in this paper.

- Our analysis examines 10 years of data (from December 1992 to February 2003). This time frame was dictated by the availability of I/B/E/S consensus recommendations. Examining longer term data, perhaps through a different data source (e.g. Zacks) could enhance our research.
- Jegadeesh (1989) examined the January effect within the context of price momentum strategies. We did not examine these effects within our data set.
- When attempting to quantify risk sources, we focused solely on the changes in I/B/E/S ratings, the French Factors (HML, SMB), and market data as the crux of

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our analysis. Other dimensions outside of these factors may have contributed to the results and returns of our constructed portfolios.

- No transaction costs. Our return numbers are calculated absent transactions costs over our observation period. If transactions costs ($.03-.05/share) were factored into our analysis, we would expect lower returns.
- Holding period. Our analysis did not take into account performance after a one-month holding period. Additional research could focus on the duration of alpha generated by the **LOW-UP** strategy.
- Changes in Dow 30 stocks over time. For the purpose of this analysis, we used the stocks in the Dow 30 as of February 2004. Over the time frame of our analysis (December 1992-February 2003), this subset of stocks was not constant.
- Finally, further research could be aimed at broadening the sample of examined stocks. While the Dow 30 represent an attractive sample because of the depth of research coverage, it may be possible to meaningfully test our hypothesis across broader market indices (e.g. S&P 500).

To benefit from the positive alpha in the **LOW-UP** portfolio, investors could execute a handful of trading strategies. A true long portfolio would consist of purchasing the **LOW-UP** portfolio of stocks on the day (or a 2-day lag if desired) of distribution of the I/B/E/S consensus data. Investors would sell this portfolio of stocks approximately one-month later on the date of distribution of the subsequent month's I/B/E/S data. At this date they would repeat the process with the new portfolio of **LOW-UP** stocks for that month. A second strategy would involve constructing a zero-cost portfolio. The portfolio construction would consist of going long the **LOW-UP** portfolio and going short and offsetting dollar amount in the poorest performing portfolio (most likely the **HIGH-DOWN**) portfolio. However, going short the **HIGH-DOWN** portfolio is not ideal, given its weak level of statistical significance. Further leveraged derivations of these strategies could also be implemented. These strategies are not without risk. Transaction costs are not factored into the return analysis, and the number of stocks in each portfolio could result in substantial risk exposure to a small number of securities in offsetting portfolios.

Portfolio considerations aside, we believe that the performance of the **LOW-UP** portfolio clearly demonstrates the power of positive analyst recommendation moves when coupled with poor price momentum. While further research is necessary to extend this analysis, behavioral finance and information based rationales suggest that this observed effect is likely to be durable.

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