Analysts, Industries, and Price Momentum

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Leslie Boni and Kent L. Womack*

Abstract

This paper examines the value of analysts as industry specialists. We show analysts create value in their recommendations mainly through their ability to rank stocks within industries. An industry-based recommendation strategy substantially improves the return to risk ratio and reduces price momentum tilt relative to portfolios that ignore industry information. An examination of the links among analyst information, aggregated at the industry level, and industry returns and industry momentum shows that industry returns precede industry-aggregated analyst upgrades and downgrades, and the short-term industry price momentum phenomenon is partly explained by returns of firms with more analyst coverage leading those with less in that industry. Recommendation information is not valuable for predicting future relative industry returns, however.

I. Introduction

With few exceptions, Wall Street analysts who write reports, estimate earnings, and issue buy and sell recommendations specialize by industry, yet previous research on analysts has done little to examine the value they provide in their role as industry specialists. Previous research has established that analysts provide at least modest incremental value to investors through their recommendations, even after controlling for a wide range of stock characteristics, other than industry, that were previously shown to have predictive value.[1,2] Not only could an industry-based analysis offer a more appropriate measure of the information value that analysts provide to investors, but it might also yield insight into the linkages among

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[1]The prior literature (Stickel (1995), Womack (1996), Barber, Lehavy, McNichols, and Trueman (2001), Jegadeesh, Kim, Krische, and Lee (2004), and Jegadeesh and Kim (2004)) has documented that returns for stocks upgraded continue to increase (after appropriate market and risk adjustments) and stocks downgraded continue to decrease for a month or more after an analyst recommendation change. But, none of these analyses examine industry-diversified portfolios or analysts' abilities to distinguish winners from losers within their industry specializations.

[2]Jegadeesh, Kim, Krische, and Lee (2004) suggest that "since we do not control for industry-related effects, it is possible that analyst recommendation revisions reflect news about a firm's competitive position in its industry" (p. 1118).

analysts' decision making and price formation and momentum. In addition, analyst information, aggregated across industries, might be a valuable predictor of future industry returns or a driver of industry momentum.

First, we focus on the information signals of future relative winners and losers that analysts provide through their recommendation revisions. Indeed, we document substantially greater value from the *relative* rankings that analysts signal within industries in which they specialize compared with a non-industry approach. While we do not exhaust all or the most optimal strategies for maximizing returns, we find that a simple self-financing strategy within each industry of buying the firms net upgraded by analysts while selling short net downgraded firms in each calendar month yields 1.23% in the next calendar month, about 30% higher than a similar non-industry approach. Returns from the industry-based strategy are also more stable over the 1996 to 2002 time frame of this study, even after controlling for the Fama and French factors and momentum. Before transactions costs, returns have a one-month Sharpe ratio (excess return divided by standard deviation of returns) of 0.49, which is almost twice as high as a similar strategy that buys upgraded stocks and sells downgraded stocks regardless of industry.

The benefits of this industry approach result primarily from forced diversification and industry neutrality. Industry risk-neutral portfolios have a significantly smaller price momentum loading in the four-factor model. We show that although analysts tend to chase price momentum (to their detriment), their expertise for investors lies primarily in their stock picking ability to rank stocks *within* the industries in which they specialize.

We further examine the returns versus the recommendation information in individual industries to gain a better understanding of analysts' decision making. We partition stocks into industries by using the Global Industry Classification Standard (GICS), which is designed and maintained by Standard & Poor's (S&P) and Morgan Stanley Capital International (MSCI) and accessible through Compustat. We apply the same self-financing long upgrades/short downgrades strategy as before, forming a separate portfolio return for each month for each of the 57 GICS classification industries.[3] We examine the seven-year time series of returns and risk characteristics for each of these 57 single industry, long-short portfolios. Each single industry portfolio is industry neutral in the sense that it invests equal dollars long and short stocks in that one industry.[4] The single industry portfolios hold only a few stocks (90% of the industry portfolios average fewer than 15 stocks long and 17 stocks short each month) and individually have greater exposure to stock-specific risk as a result. Despite the expected increase in the time-series variance of returns, the single industry portfolio returns are nominally positive for 54 out of 57 industries and significantly positive statistically for a substantial number of industries (16 out of 57). Perhaps more interestingly, none

[3]Although there are 59 industries using the GICS industry classification, two of the industries are excluded from this portion of the study as they experience recommendation changes only for a few months during the 1996–2002 time period of our study.

[4]King (1966) provides one of the earliest analyses of industry risk factors and security returns. In that spirit, some practitioners identify industry risk factors and consider portfolios to be industry neutral if they have a zero loading on these factors. We do not employ industry risk factor regression techniques.

of the 59 industry time series have returns that are significantly negative. For half of the industries, portfolio returns have a one-month Sharpe ratio of 0.11 or more.

Previous authors have documented a link between price momentum and analysts' earnings forecasts and recommendations (e.g., Chan, Jegadeesh, and Lakonishok (1996), Hong, Lim, and Stein (2000), and Jegadeesh, Kim, Krische, and Lee (2004)). Hence, analysts' recommendation information aggregated at the industry level could also help our understanding of price momentum, one of the largest challenges to market efficiency. Moskowitz and Grinblatt (1999) argue that price momentum is largely an industry-driven phenomenon. We examine whether momentum in analysts' recommendations forecasts industry price momentum. The linkage could also exist in the opposite direction: analysts in their recommendations possibly chase industry price momentum. A better appreciation of the lead-lag relationships between industry information and prices also could be useful in devising industry rotation strategies, in which investors overweight the stocks of those industries that they expect to outperform the market. For example, an apparent flurry of upgrades from analysts in a particular industry could signal future abnormal returns for that industry. More generally, analysts' recommendation information, aggregated at the industry level, may forecast hot and cold industries.

Using the GICS industry classification over the 1996–2002 time frame, we find evidence of only short-term (one-month) industry price momentum. We show that this short-term industry price momentum phenomenon may be driven, at least in part, by returns of firms with more analyst coverage leading the returns of firms with less coverage in the same industry, consistent with Hou (2004). Generally, we find that industry-aggregated upgrade and downgrade information measures exhibit positive serial correlation over short-term (several months) horizons. Our analysis does not suggest, however, that analyst recommendations, aggregated by industry, can be used to forecast future industry returns. Specifically, industry rotation strategies of buying stocks in net upgraded industries and shorting stocks in net downgraded industries generally offer returns of little statistical or economic significance.

The rest of the paper proceeds as follows. Section II presents the dataset and descriptive statistics. Section III discusses the motivation for and empirical results of the analyses of the value of analysts' recommendations within their industry specializations. Section IV discusses the value of the industry-aggregated recommendation measures and their relationship with industry price momentum. Section V discusses the implications of our findings for comparisons of various types of firms that provide research.

II. The Data and Descriptive Statistics

Our dataset consists of IBES data on analyst recommendations and consensus levels, Center for Research in Security Prices (CRSP) monthly stock returns and market capitalizations, and industry codes as defined by GICS, S&P, and MSCI. The time frame for our study is 1996 through 2002.[5]

[5]We choose January 1996 as the first month for our study for several reasons. IBES recommendation data are somewhat problematic in that new observations of analyst recommendations do not

The superiority of using the GICS classification scheme for various financial and accounting research applications has been documented by Bhojraj, Lee, and Oler (2003).[6] We will show that the GICS industry classification also provides a good partition defining industries as analysts define themselves by their coverage choices.

We include all NYSE, AMEX, and Nasdaq companies that have CRSP monthly returns and can be matched with a GICS industry code using Compustat. We include CRSP ordinary shares and ADRs and exclude closed-end funds, shares of beneficial interest, and units. Specifically, we include CRSP share codes of 10, 11, 12, 18, 30, and 31. We include ADRs because a substantial portion (more than 50%) has analyst coverage.

Because the trading strategies we examine are long-short portfolio strategies, we exclude stocks priced less than $5/share. This constraint is motivated by the fact that stocks priced under $5/share are difficult to borrow and thus difficult to short sell (e.g., see D'Avolio (2002)).[7]

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 from the previous 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 10,469 companies in our dataset, 2,676 are neglected firms, i.e., they have no recommendation or consensus level data per IBES.

As Table 1 shows, there are 169,127 recommendations in the 1996 to 2002 time frame. Of these, 116,528 can be classified as recommendation changes from one rating level to another. The dataset also includes 52,599 first recommendations. These are recommendations for which a previous rating level is not identifiable, either because a prior recommendation does not exist (i.e., an analyst is initiating coverage) or because the company/analyst pair cannot be matched to an earlier rating in the database. In addition to changes in recommendations, IBES

indicate the analyst's prior recommendation for that stock. Although the data can be searched for the most recent observation by the analyst for that stock, absence of a prior recommendation can result if either the analyst is initiating coverage or the brokerage firm had not yet begun to contribute recommendation information to IBES when the analyst made a prior recommendation. IBES recommendation data exist for some brokerage firms prior to 1996 but is somewhat sparse, particularly prior to 1995. Choosing 1996 as the starting point permits the search for prior recommendations in 1995 (and earlier). We have IBES and CRSP data through December 2002.

[6]Bhojraj, Lee, and Oler (2003) compare four industry classification schemes: i) the Standardized Industry Classification (SIC); ii) the North American Industry Classification System (NAICS); iii) Fama and French (1997) groupings; and iv) GICS. They examine a variety of capital market research applications and conclude that the GICS classification is superior for identifying firms with the industry peers.

[7]Earlier versions of this paper included stocks less than $5/share and also incorporated recommendation data from Validea.com, a now defunct Internet startup company. The current version uses only U.S. IBES recommendation data to permit academics and practitioners to replicate our results.

also includes some recommendation reiterations, which we exclude from our detail recommendation dataset.

TABLE 1

Transition Matrix of Recommendations and Three-Day Event Excess Returns (1996–2002)

Panel A. Number of Recommendations

From IBES Code \ To IBES Code	1 Strong Buy	2	3 Hold	4	5 Sell	All
1 Strong Buy	—	21,048	14,248	337	283	35,916
2	19,479	—	24,755	873	329	45,436
3 Hold	9,487	18,065	—	2,725	1,124	31,401
4	161	453	1,598	—	116	2,328
5 Sell	156	243	951	97	—	1,447
First Recommendations	19,268	21,680	10,823	467	361	52,599
All	48,551	61,489	52,375	4,499	2,213	169,127

Panel B. Mean Three-Day Event Excess Returns (in percent)

From IBES Code \ To IBES Code	1 Strong Buy	2	3 Hold	4	5 Sell
1 Strong Buy	—	**−3.76**	**−5.56**	**−6.32**	**−3.32**
2	**3.02**	—	**−4.70**	**−3.87**	**−2.22**
3 Hold	**3.03**	**2.95**	—	**−2.34**	**−2.83**
4	**4.43**	**1.83**	**1.75**	—	**−1.93**
5 Sell	**1.70**	0.24	**1.39**	0.01	—
First Recommendations	**1.79**	**0.73**	**−0.66**	**−0.86**	**−1.32**

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. First Recommendations are the first observation of an analyst at a brokerage firm for a particular stock. Panel B reports the means of percentage three-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.

Table 1, 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 1 shows that downgrades (56% of recommendation changes) actually *exceed* upgrades (44% of recommendation changes). In the long run, we would expect the number of upgrades to equal the number of downgrades. The higher percentage of downgrades is likely the result of the large number of initial recommendations (which we cannot identify as upgrade or downgrade) during the 1996–2002 period that are strong buys and then later downgraded in our time frame.

It is also worth noting the magnitude of the three-day market-adjusted returns for the various change categories shown in Table 1, Panel B for the years 1996–2002. 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 in Womack (1996). [8]

[8]These returns are significantly higher than the 1.06% to 1.48% range reported by Barber, Lehavy, McNichols, and Trueman (2001) for the 1985 to 1996 time period in the Zacks data. There are two possible explanations for the difference. The Zacks database, while including most of the significant U.S. 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 returns with a delay relative to the actual event dates.

Brokerage firm characteristics are shown in Table 2. The largest 20 firms, ranked by number of companies for which they provide coverage, account for 44% of the recommendations. S&P, although not a brokerage firm, contributes its recommendations to IBES and ranks 17th in the number of companies covered. It is the only firm in the top 20 whose sum of underperform and sell recommendations exceeds 10% of all its recommendations during the time period.[9]

TABLE 2

Recommendation Changes and the Brokerage Firms Making Them (1996–2002)

					Broker's Recommendations		
	Broker Name	Cos.	Analysts	Industry Presence	Recom-mendations	Strong Buy (%)	Underperform and Sell (%)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1	Salomon Smith Barney	2,343	365	35.4	6,515	29.5%	4.8%
2	Merrill Lynch	2,205	430	36.2	6,225	26.1%	3.3%
3	Credit Suisse First Boston	1,967	287	28.9	4,519	14.7%	4.1%
4	Morgan Stanley	1,849	269	29.3	5,291	18.2%	5.4%
5	Goldman Sachs	1,781	228	28.1	4,665	24.7%	4.4%
6	Lehman Brothers	1,778	218	24.8	4,054	29.5%	6.0%
7	Banc of America Securities	1,691	165	22.7	3,215	57.8%	1.6%
8	Bear Stearns	1,617	194	23.5	3,610	31.3%	3.6%
9	UBS Warburg	1,562	219	22.8	2,982	0.0%	2.8%
10	Donaldson	1,546	110	22.4	3,845	14.1%	3.6%
11	CIBC World Markets	1,527	161	21.2	3,270	23.9%	4.2%
12	J.P. Morgan	1,510	249	22.6	3,372	41.0%	5.0%
13	Deutsche Banc Alex Brown	1,473	222	22.7	3,144	17.4%	2.1%
14	Prudential Securities	1,343	136	19.4	3,410	38.7%	2.4%
15	Alex Brown	1,339	134	21.6	2,751	24.9%	0.9%
16	Robertson Stephens	1,218	136	14.8	2,784	16.5%	0.4%
17	Standard and Poor's	1,166	70	19.6	2,705	11.8%	13.8%
18	Dain Rauscher Wessels	1,109	108	12.8	2,286	25.6%	0.3%
19	A.G. Edwards & Sons	1,095	105	18.4	3,983	26.9%	6.5%
20	ABN AMRO	1,041	108	17.2	2,105	40.1%	1.9%
Ranked 1–20 by Number of Cos. Covered		5,823	3,914	23.2	74,731	25.5%	4.0%
Ranked > 20 by Number of Cos. Covered		7,479	5,831	2.9	94,396	31.3%	3.9%
All Brokerage Firms		7,793	9,745	3.7	169,127	28.7%	4.0%

Table 2 shows 169,127 recommendation changes by sell-side analysts in the time period 1996 to 2002 according to the IBES Detail Recommendation file. Column 2 shows the number of companies that are followed during the seven-year period by the largest 20 U.S. brokerage houses and collectively the remaining 485 brokerage firms and subsidiaries listed in IBES. Column 3 gives the total number of analyst IDs listed in IBES per firm during the seven-year period. When an analyst changes firms, he or she may be counted again at another brokerage firm. Therefore, the total number of analysts is almost surely an overestimate of the actual number of analysts working at sell-side firms. For column 4, a brokerage firm's industry presence is calculated for each GICS industry, and is defined as the number of companies followed (with at least one recommendation change) in the industry by the broker, divided by the total number of companies in that industry with IBES recommendation coverage. Column 4 shows the broker's industry presence averaged across all industries that broker covers. Column 5 shows the number of recommendation changes or first recommendations made by the brokerage firm's analysts. Percent Strong Buy and Percent Underperform and Sell are as a percent of the firm's recommendations over the period as categorized by IBES.

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. Analysts tend to specialize within one or several industries to provide investment advice to investor clients. Our objective is to partition and examine companies in the industry groups that are as similar as possible to how they are

[9]There is little variation across brokerage firms in the average consensus level rating of companies they cover (the average is consistently about 2.0, a buy rating) or the average number analysts that cover each company (nine to 10 analysts). The top 20 brokerage firms tend to cover larger companies. The CRSP NYSE market capitalization decile average for all stocks in our universe is 3.6. For analyst-covered firms, it is 5.0 and for stocks followed by the top 20 brokerage firms, it is 5.9. While our universe includes a broad cross section of stocks from all markets, we choose to use CRSP NYSE market capitalization breakpoints for comparison with other studies.

covered by sell-side analysts, recognizing that no one partition will fit all analysts and firms. The annual *Institutional Investor* poll asks buy-side to rate sell-side analysts in roughly 70 industry categories. Therefore, we use the GICS codes at the 59-industry level, dividing the companies in our dataset into 59 distinct industry groups. The largest brokerage firms cover stocks in almost all 59 GICS industry groups.

For each brokerage firm for each industry, we calculate industry presence, which we define as the number of companies that the brokerage firm covers divided by the total number of companies in that industry that have any recommendation coverage (per IBES). Table 2 reports the average industry presence for each brokerage firm, which is the average of all industries the firm covers. Merrill Lynch has the highest average industry presence, covering on average 36.2% of the companies in an industry in which it has an analyst. The top 20 firms (including S&P) average 23.2%. The remaining firms have much less of a presence, averaging only about 3%.

Table 3 demonstrates that the 59-industry GICS code partition provides a good proxy for how analysts specialize by industry. Analysts in the largest 20 firms cover approximately 10 companies. On average, the companies an individual analyst covers fall into one to three GICS industries. We define the analyst's most covered industry as the industry into which the largest number of companies the individual analyst covers falls. Table 3 shows that the percentage of all companies an analyst covers that are in one GICS industry averages 81% for analysts at the 20 largest brokerage firms and 76% for analysts at brokerage firms overall. We conclude therefore that GICS quite accurately describes industries as analysts define them by their coverage decisions.

The 59 GICS industries are listed in the Appendix.[10] The average number of companies per industry is 177. Banks is the largest (and most unusual) industry with 1,224 companies. No industry has analyst coverage for every stock, but all industries have at least some analyst coverage. On average, about 75% of companies within an industry have coverage by at least one analyst. The average analyst coverage per covered company (not shown) ranges from 2.0 to 9.6 analysts. The average consensus level rating for all stocks in all industries (not shown) is close to a buy (IBES rating level = 2) with little time-series variation.[11]

III. Within-Industry Analyst Rankings and Industry-Neutral Portfolios

A. Motivation and Portfolio Construction

Prior studies have documented predictable and economically significant returns after recommendation changes. To what extent do abnormal returns from analyst recommendations result from industry expertise, namely the consistent identification of over- and underperforming stocks in the analyst's coverage universe?

[10]The Appendix also reports portfolio results discussed in Section III.

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

TABLE 3

Analysts' Coverage Choices Relative to GICS Industry Partitions (1996–2002)

	No. of Analysts	Companies Covered per Analyst	GICS Industries Spanned per Analyst	Ratio of No. of Companies Analyst Covers in His/Her Most Covered GICS Industry to Total No. of Companies Analyst Covers			
		(mean)	(mean)	(25th percentile)	(mean)	(median)	(75th percentile)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Top 20 Brokerage Firms							
If the Analyst Covers:							
1–10 companies	2,570	4.1	1.6	0.67	0.85	1.00	1.00
11–20 companies	902	14.8	3.1	0.58	0.74	0.80	0.93
21–30 companies	277	24.4	4.0	0.54	0.71	0.74	0.90
31–40 companies	105	35.2	5.5	0.48	0.65	0.67	0.81
> 40 companies	60	97.4	16.7	0.18	0.46	0.47	0.68
All	3,914	10.3	2.5	0.63	0.81	0.91	1.00
Companies covered	5,823						
Panel B. All Brokerage Firms							
Analyst Covers:							
1–10 companies	6,677	4.1	1.8	0.60	0.81	1.00	1.00
11–20 companies	2,096	14.5	3.7	0.47	0.68	0.71	0.92
21–30 companies	616	24.4	5.1	0.45	0.64	0.64	0.88
31–40 companies	214	34.7	6.7	0.38	0.59	0.60	0.81
> 40 companies	142	78.5	14.9	0.19	0.45	0.40	0.67
All	9,745	9.4	2.7	0.53	0.76	0.86	1.00
Companies covered	7,793						

Table 3 gives statistics for analyst coverage and the efficacy of GICS industry codes as the map for how sell-side analysts' coverage choices define them as industry specialists. Panel A shows statistics for analysts at the 20 brokerage firms that cover the largest number of stocks as shown in Table 2. Panel B provides data for analysts at all brokerage firms. In each panel, analysts are partitioned by the number of companies they cover in the 1996 through 2002 time frame, with column 1 showing the number of analysts in each partition. 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 the 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 the analyst covers. Columns 4–7 indicate for each analyst partition the 25th percentile, mean, median, and 75th percentile points for this fraction.

To answer this, we construct two variations of long-short (i.e., self-financing) portfolio strategies that are based on recommendation information. For each strategy, stocks are selected using information collected over month $t-1$ and hence are available at the end of month $t-1$. One-month holding period returns are calculated for month t. We then examine the time series of returns and risk characteristics for each strategy.

Strategy Name	Long Side	Short Side
Consensus Level	Stock with best consensus level in each industry	Stock with worst consensus level in each industry
Recommendation Changes	All net upgraded stocks in the industry	All net downgraded stocks in the industry

In each strategy, the investor buys all stocks that meet the long-side criteria, financed by selling short all stocks that meet the sell-side criteria. Monthly portfolios include an industry only if the industry has at least one stock that meets the long-side criteria and at least one stock that meets the short-side criteria that month in that industry. Industries are equal dollar weighted within portfolios.

In the Consensus Level Strategy, the stock of 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 which stock has the highest or lowest consensus level in an industry in a month, the average return of all tying stocks is used in that portfolio component that month.

To examine portfolio strategies based on recommendation changes, we define a measure called AgChange (for aggregate change). It is calculated at the end of each month and is the sum of the number of analyst recommendations (from all analysts) that are upgrades during the month less the number of downgrades. For example, if Microsoft receives six analyst upgrades and two analyst downgrades in a month, Microsoft's AgChange that month equals +4. Using this simple measure, we refer to stocks with an AgChange greater than zero as net upgraded in a month. Similarly, we call stocks with an AgChange less than zero net downgraded. Using the AgChange measure, the Recommendation Changes Strategy portfolios take long positions in net upgraded stocks and short positions in net downgraded stocks. Because an industry can be included only if the industry has at least one stock net upgraded and at least one stock net downgraded that month, this strategy (as in the Consensus Level Strategy) forces industry-specific risk to be neutralized.

As discussed in the previous section, a substantial percentage of recommendations in the dataset are first recommendations, which may represent initiations of coverage or recommendations of analysts whose prior ratings cannot be matched in the database. We exclude these observations from the AgChange calculation. The reason is that a large percentage (31%) of our first recommendations are buy recommendations. An initial buy in our dataset may represent a bona fide new recommendation or it may have previously been a strong buy (hence, a downgrade) or previously a hold recommendation (hence, an upgrade). Ambiguous (weaker) returns relative to those for known upgrades and downgrades for first recommendations in the last row of Table 1 corroborate our judgment to exclude these observations for the AgChange calculation.

In each industry, more than one stock may meet either the long- or short-side criteria each month. We examine the impact of stock equal dollar weighting versus market capitalization (value) weighting within the industry allocations. Equal weighting prevents recommendations for companies with larger market capitalization from overshadowing recommendations for smaller companies. We also examine portfolios in which stock selection is constrained to the largest market capitalizations (CRSP NYSE decile) and levels of analyst coverage.

We also estimate two monthly time-series regressions for each portfolio, deriving excess returns after the Fama-French factors, with and without the momentum factor, as in Barber et al. (2001, p. 543).[12] First, using portfolio one-month post-formation return as the LHS variable, we estimate the three-factor model of Fama and French (1993), where the three factors are i) the excess market return $(R_m - R_f)$; ii) the return from a value-weighted, self-financing portfolio, which is long small-cap stocks and short large-cap stocks (SMB); and iii) the return from a value-weighted, self-financing portfolio, which is long value stocks and

[12]We form portfolios using recommendation information at the end of each of 83 calendar months (January 1996 through November 2002). No portfolio is formed using December 2002 recommendation information as we do not have January 2003 CRSP data to use for post-formation month returns.

short growth stocks (HML).[13] Second, we estimate a four-factor model, which is identical to the three-factor model, with an equally-weighted momentum portfolio return added as a fourth factor (MOM). The momentum portfolio we use for comparison is of Jegadeesh and Titman's (1993) design, with $J = 11$ and a one-month skip. It is long the best 30% and short the worst 30% of stocks.

B. Results for Industry-Neutral Portfolios

Table 4 shows the mean, standard deviation, and monthly Sharpe ratio of one-month post-formation returns for each of the recommendation-based portfolio strategies.[14] Panel A shows results when stocks are equal weighted and Panel B when stocks are value weighted in portfolios.

Panel A of Table 4 reports the mean return from using the Consensus Level Strategy (i.e., Best Stock–Worst Stock in each industry) as −0.256% in the calendar month following portfolio formation, but it is 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 be based on recommendations that may have been issued many months prior. If post-recommendation returns trend in the predicted direction for only a few weeks or months as earlier papers have reported, we would expect little value from consensus levels that add a few changes each month to otherwise stale ratings. The ratio of stocks long versus short averages 3 to 1 in the Consensus Level Strategy portfolios. This occurs as the result of more stocks tying at the best extreme consensus level in an industry (usually 1, a strong buy) than at the worst level.

Panel A, Table 4 shows that the Recommendation Changes Strategy (labeled Industry-Weighted Changes Strategy) provides substantially higher returns in the first post-formation month than does the Consensus Level Strategy. It has a significant mean return of 1.235% and a higher monthly Sharpe ratio of 0.49 after excluding stocks with prices less than $5 per share.[15,16] Panel B shows that weighting stocks by market capitalization reduces the mean return of the change-based portfolios to 0.801% per month (still statistically significant) and the Sharpe ratio to 0.25. For the changes strategy, the ratio of stocks long versus short is slightly less than 1 to 1, which is consistent with data in Table 1 that show analysts are about equally likely to upgrade or downgrade stocks during the 1996 to 2002 time frame.[17]

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

[14]The interest rate used to calculate Sharpe ratios is the one-month Treasury bill rate (from Ibbotson Associates).

[15]If traders are unable to incorporate recommendations issued the last trading day of the month in this calendar-month strategy, the mean return is reduced by seven basis points per month. Since most recommendations occur at the beginning of the day, we do not consider this possibility likely.

[16]Earlier versions of this paper, using the Validea data for recommendations and including stocks priced at less than $5/share resulted in a 1.44% monthly return and a 0.57 monthly Sharpe ratio. Using the U.S. IBES data and including stocks priced less than $5/share increases the mean return to 1.59% per month and the monthly Sharpe ratio to 0.63.

[17]No month has fewer than 42 industries represented in the recommendation change portfolios. The median and mean number of industries represented in the changes portfolio over the 83-month sample is 48 (or 80%) of the 59 industry groups.

TABLE 4

Percentage Monthly Returns and Regression Estimates for Long-Short Recommendation Portfolios (1996–2002)

	Mean Return	Std. Dev.	Monthly Sharpe Ratio	Intercept from F&F	Intercept from 4-Factor	Coefficient Estimate for 4-Factor Model $R_m - R_f$	SMB	HML	MOM	Stocks Long	Stocks Short	No. of Industries $\mu > 0$	$\mu = 0$	$\mu < 0$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)		
Panel A. Stocks Equal Weighted														
Consensus Level Strategy:	−0.256	2.86	−0.22	−0.231	−0.491	0.070	0.071	−0.033	0.177	396	131	4	50	5
Best–Worst	*−0.82*			*−0.73*	*−1.64*	*0.96*	*1.02*	*−0.36*	***3.78***					
Industry-Weighted Changes Strategy:	1.235	1.77	0.49	1.291	1.165	−0.029	−0.091	−0.039	0.085	374	456	16	42	0
Stocks Net Up–Stocks Net Down	***6.36***			***6.55***	***6.00***	*−0.61*	***−2.01***	*−0.65*	***2.81***					
Unweighted Changes Strategy	0.948	2.11	0.28	0.932	0.591	0.081	0.012	0.094	0.232	374	456	— not applicable —		
Stocks Net Up–Stocks Net Down	***4.09***			***3.89***	***3.23***	***1.79***	*0.28*	***1.67***	***8.09***					
Unweighted Changes Less	−0.286	1.74		−0.358	−0.573	0.110	0.103	0.132	0.146			— not applicable —		
Industry-Weighted Changes	*1.47*			***−1.89***	***−3.47***	***2.70***	***2.67***	***2.59***	***5.64***					
Panel B. Stocks Value Weighted														
Consensus Level Strategy:	0.330	3.25	−0.01	0.370	0.042	0.092	0.081	−0.059	0.223	396	131	9	48	2
Best–Worst	*0.92*			*1.05*	*0.13*	*1.14*	*1.06*	*−0.58*	***4.34***					
Industry-Weighted Changes Strategy:	0.801	1.78	0.25	0.886	0.822	−0.101	−0.115	−0.077	0.044	374	456	10	48	0
Stocks Net Up–Stocks Net Down	***4.10***			***4.68***	***4.25***	***−2.12***	***−2.56***	*−1.29*	*1.44*					
Unweighted Changes Strategy	0.182	2.90	−0.06	0.164	−0.061	0.031	−0.026	0.099	0.153	374	456	— not applicable —		
Stocks Net Up–Stocks Net Down	*0.57*			*0.50*	*−0.19*	*0.40*	*−0.35*	*1.00*	***3.06***					
Unweighted Changes Less	−0.619	2.79		−0.722	−0.884	0.132	0.089	0.176	0.110			— not applicable —		
Industry-Weighted Changes	***−2.01***			***−2.30***	***−2.81***	***1.71***	*1.22*	***1.82***	***2.23***					

Table 4 shows percentage monthly returns (column 1), standard deviations (column 2), monthly Sharpe ratios (column 3), and estimates from time-series regressions of calendar-time portfolios. For the first two strategies in each panel, portfolios are formed using the recommendation portfolio strategies defined in Section III.A. Investors rebalance a single portfolio each month, equal weighted by industry. For the third strategy in each panel, portfolios are formed using the recommendation changes criteria, but industry classifications are ignored. For the fourth strategy in each panel, portfolios are long the unweighted changes strategy and short the industry-weighted changes strategy. Column 4 shows the intercept from the Fama and French three-factor model. Columns 5–9 show estimates for the four-factor model. *t*-statistics (in italics) in bold indicate estimates that are significant at the 10% level. Columns 10 and 11 show the average number of stocks long and short per month. Column 12 shows the number of industries whose single industry long-short portfolios over the time period have returns that are greater than ($\mu > 0$), equal to ($\mu = 0$), or less than ($\mu < 0$) zero at the 10% significance level.

To highlight the impact of equal industry weighting, the third row of results in each panel of Table 4 (labeled Unweighted Changes Strategy) shows what happens when portfolios are formed using the changes criteria for stock selection but ignoring industry classification. Stocks are simply equally weighted in the long and short portfolios without regard for industry. Panel A shows that this strategy has a lower mean return (0.948% versus 1.235%), a greater time-series variance of monthly returns, a lower Sharpe ratio, and a reduced four-factor model intercept relative to its equal industry-weighted counterpart. Panel B of Table 4 shows that the mean return and regression intercepts are not significant when stocks are value weighted and not industry weighted.

To further analyze the impact and investment value of equal industry weighting, we analyze the time series of return differences between the unweighted and industry-weighted strategies. The focus is on understanding the sizable difference in the monthly alpha (intercept) in the four-factor model between the two weightings (e.g., in Panel A, $0.591\% - 1.165\% = -0.573\%$). Specifically, we create a difference portfolio each month that is long the unweighted long-short portfolio and short the equal industry-weighted long-short portfolio. It is worth emphasizing that the unweighted and industry-weighted strategies are long and short the same stocks, and the equal industry weighting only forces equal industry weights.[18] The last row in each panel in Table 4 reports the monthly raw return mean, three-factor intercept, and regression estimates for the four-factor model. These are just the differences between the third and second strategies in the panel (with apparent small differences due to rounding off). What is interesting are the t-statistics. With the exception of the small minus big factor for the four-factor regression in Panel B, the unweighted strategy has significantly higher loadings for each of the four factors. Thus, the benefit of equal industry weighting does not come from smaller stocks, a value orientation, or participating in momentum strategies. Previous research (e.g., Jegadeesh, Kim, Krische, and Lee (2004)) shows that analysts tend to chase price momentum. The highly significant loadings on the price momentum factor in the four-factor regressions (and the large difference in intercepts between the three- and four-factor models) suggest that forcing equal industry weighting reduces the impact from analysts' tendency to chase momentum and improves the incremental value of their recommendations.

To better illustrate the low variance of the time series of returns for the changes-based strategies, Figure 1 shows the individual monthly returns for the industry-weighted and unweighted changes strategies from Panel A of Table 4. For comparison, Figure 1 also shows monthly returns from Jegadeesh and Titman's (1993) price momentum ($J = 6/K = 6$, skip one month) portfolios. Before transactions costs, the returns from the industry-weighted, changes-based strat-

[18]As an alternative, it is possible to construct unweighted portfolios, which have slightly more stocks in the long and short portfolios each month on average. Specifically, all net upgraded and net downgraded stocks could be included in the long and short portfolios. As discussed in the previous section, in the equal industry-weighted portfolios, stocks are included only if there is at least one stock in the same industry with net recommendation change of opposite direction that month. As a robustness check, we formed these alternative portfolios. This alternative version of the unweighted strategy increased the number of stocks long and short by 3% versus the results reported in Table 4. Signs and statistical inferences of parameter estimates were unchanged from those reported in the third and fourth rows of Panels A and B of Table 4.

egy have a one-month Sharpe ratio almost twice as high as a similar unweighted strategy and six times larger than the price momentum strategy.

The comparison of the recommendation-based portfolio strategies to momentum in Figure 1 is not exactly an apples to apples comparison for several reasons. First, the momentum strategy includes stocks that receive no analyst coverage. Second, stocks in the momentum strategy are not equal industry weighted. [19] To determine how much value is due to different stocks, we reexamined the momentum strategy using only stocks covered by analysts. The number of stocks bought and sold dropped from 1,025 stocks (number long plus number short) per month to 789. The mean monthly return was unchanged at 0.9%, the standard deviation increased slightly (to 7.8% versus 7.4% when all stocks were used), and the monthly Sharpe ratio dropped to 0.06 as a result. We then took these momentum portfolios (constructed from stocks covered by analysts) and equal industry weighted the stocks in the long and short portfolios. The mean monthly return decreased to 0.4%, and the monthly Sharpe ratio dropped to 0.00. This comparison clarifies that even though analysts have a tendency to recommend momentum stocks, the real value of their recommendation changes arises from their ability to force rank stocks within the industries using non-momentum information.

The last three columns of Table 4 summarize the means of the time series of one-month returns of the 58 single industry portfolios. [20] Of course, these single industry portfolios hold far fewer stocks. For example, 90% of the Changes Strategy single industry portfolios average fewer than 15 stocks long and 17 stocks short per month, and 50% have fewer than seven each on the long- and short-side per month. The single industry portfolios thus have greater exposure to stock-specific risk. Each of the single industry portfolios is industry neutral, however, in the sense that it is equally long and short stocks in that one industry. Information on mean returns, monthly Sharpe ratios, and portfolio composition of the single industry, long-short portfolios, formed using the equal industry-weighted Changes Strategy, is provided in the Appendix. Interestingly, for over 90% of the industries, the average reported one-month return for the 1996–2002 time frame is positive. As Table 4 shows, 16 out of 58 are statistically significantly positive at the 10% level. Interestingly, none of the individual industry time-series means is significantly negative.

As evidence of the importance of diversification across industries, we examine the use of alternative industry partitions for the Changes Strategy portfolios. We compare our earlier analysis in which we used a 59-industry partition to two coarser GICS partitions (i.e., the 10-category sector partition and the 23-category industry group partition) as well as to the finest GICS partition (the 122-category sub-industry partition). Table 5 reports results for these portfolios. For comparison, Table 5 also shows the 59-category industry partition and the no partition (i.e., the unweighted Changes Strategy) results from Table 4. For each of the

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[19]We thank the referee for this insight and for suggesting several variations on the Jegadeesh and Titman (1993) strategy.

[20]One industry, GICS Code 203050, Transportation Infrastructure, has so few companies followed by analysts (three) that, using some of the recommendation measures, portfolios cannot be formed in more than one month. Similarly, in Table 5, when the GICS 122-category partition is analyzed, only 118 of the 122 industry categories have enough recommendations to permit portfolio formation for more than one month.

FIGURE 1

Time-Series Returns of Recommendation and Momentum Portfolios

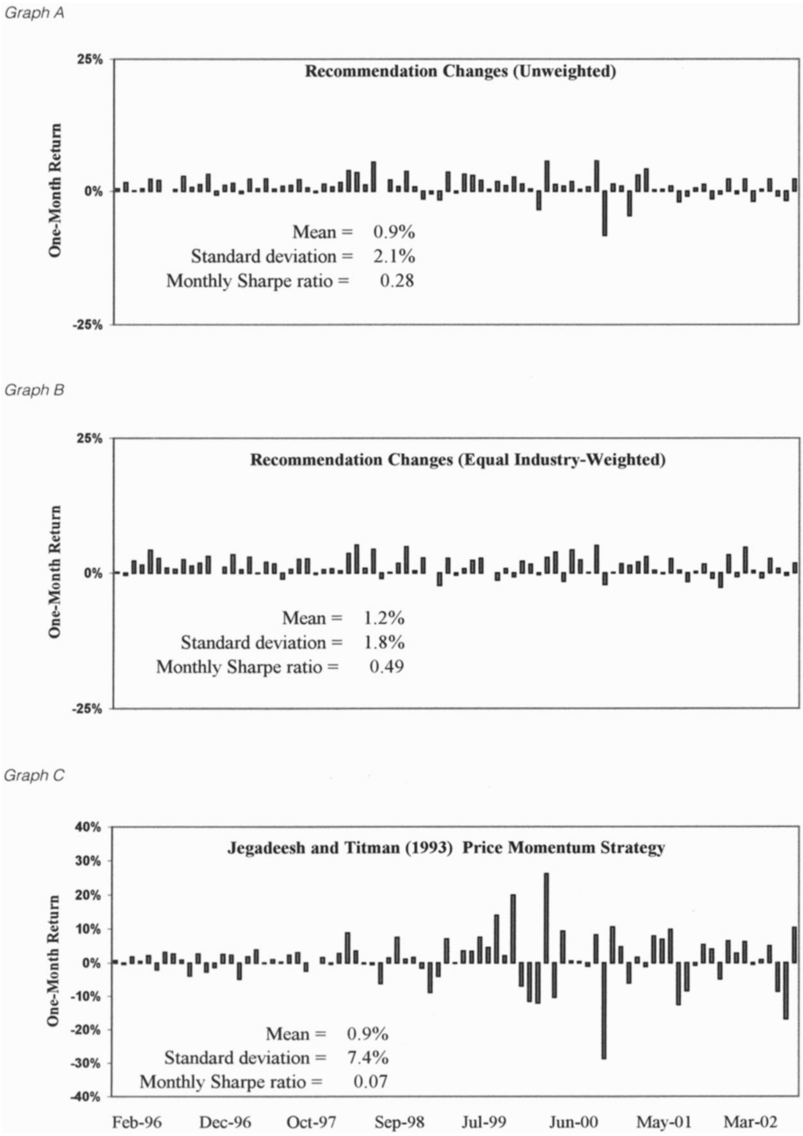


Figure 1 shows the time series of one-month returns from portfolios formed using recommendation and price momentum strategies. See Table 4. Recommendation Changes portfolios are the unweighted (Graph A) and equal industry-weighted (Graph B) long-short portfolio strategies. Jegadeesh and Titman (1993) momentum portfolios are $J = 6/K = 6$, best 10% stocks minus worst 10% stocks, skip one month, long-short portfolios.

GICS partitions, when stocks are equally weighted within industry partitions (i.e., Table 5, Panel A), raw returns and regression intercepts are positive and statistically significant. The key result is that the Sharpe ratio of the long-short strategy increases as the industry partitioning increases from one to 10 categories to 59 industry categories. Panel B of Table 5 shows that when stocks are value weighted, mean returns and factor-model alpha intercepts are reduced substantially when industries are weighted using the coarsest, the unweighted (no partition), and the 10-group industry partition (sector) strategy relative to the finer industry partitions. It is also worth noting that the loading on the momentum factor in the four-factor model decreases for the finer partitions as well.

It is well known that post-recommendation drift is greater for stocks with smaller market capitalizations. Hong, Lim, and Stein (2000) link the phenomenon of price momentum with analyst following, giving support to the hypothesis of Hong and Stein (1999) that momentum is a symptom of investors' collective underreaction 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.

To this point in the analysis, we have allowed investors to construct portfolios from any stocks priced at \$5/share or higher. We imposed this price constraint because prior authors have documented the difficulties of shorting stocks priced at less than \$5/share. While this constraint also eliminates many of the smallest stocks that would have unsatisfactory liquidity for an institutional investment strategy, our results documented thus far still benefit from small market cap firms (priced greater than \$5/share). Therefore, we now examine the effects of limiting strategies to larger (and arguably more liquid) stocks, which we proxy for by using CRSP NYSE market cap (size) deciles. As analyst coverage and market cap are positively correlated, we also control for the effect of greater analyst competition or coverage.

Figure 2 shows, for the Changes Strategy, the mean one-month adjusted returns (i.e., intercepts from Fama and French three-factor regressions) as a function of market cap (i.e., CRSP decile) and analyst coverage. Portfolio returns are from the equal industry-weighted portfolios, consistent with Table 4, row 3. Graph A of Figure 2 reports results when stocks are equal weighted within the industries. Results for portfolios with stocks that are value weighted are shown in Graph B.

Figure 2 shows that returns decrease as market cap increases and as analyst coverage increases. For example, the back left column of Graph A shows that the Fama and French three-factor intercept, when all stocks are available for the investment strategy (i.e., stocks from all CRSP size deciles and with the coverage of at least one analyst), is 1.29% per month, consistent with Table 4. The next column, immediately to the right on the back row, shows that excluding stocks with analyst coverage of less than three analysts reduces the adjusted return of the strategy to 1.18% per month. Similarly, moving forward by one row shows the reduction in return when stocks with market caps that place them in the smallest two CRSP NYSE size deciles are excluded.

Not surprisingly, high market capitalizations and competition among analysts within their industries both mitigate (but do not eliminate) realizable returns from using recommendation information. However, even when portfolios are re-

TABLE 5

Comparison of Long-Short Recommendation Portfolios for Various Degrees of Coarseness of the GICS-Code Partitions

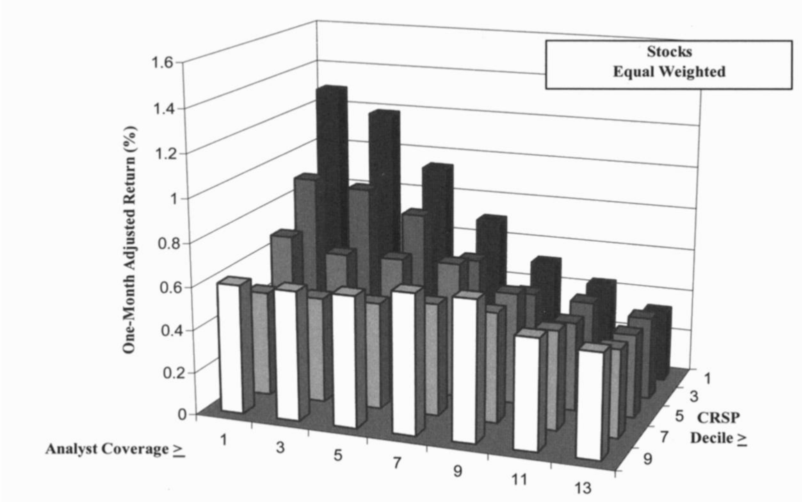
	Mean Return	Std. Dev.	Monthly Sharpe Ratio	Intercept from F&F	Intercept from 4-Factor	Coefficient Estimate for 4-Factor Model $R_m - R_f$	SMB	HML	MOM	Stocks Long	Stocks Short	No. of Partition Members $\mu > 0$	$\mu = 0$	$\mu < 0$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)		
Panel A. Partitions Equal Weighted; Stocks Equal Weighted; Various Degrees of Coarseness of the GICS-Code Partitions														
No partition: stocks equal weighted without regard for GICS code	0.948 ***4.09***	2.11	0.28	0.932 ***3.89***	0.591 ***3.23***	0.081 ***1.79***	0.012 *0.28*	0.094 ***1.67***	0.232 ***8.09***	374	456	1	0	0
Coarsest GICS partition (10 sectors)	0.896 ***4.31***	1.89	0.28	0.908 ***4.30***	0.733 ***3.65***	0.033 *0.67*	−0.094 ***−2.02***	0.040 *0.65*	0.118 ***3.77***	382	469	8	2	0
Finer GICS partition (23 industry groups)	1.016 ***5.36***	1.73	0.38	1.049 ***5.38***	0.892 ***4.79***	−0.006 *−0.13*	−0.055 *−1.27*	−0.003 *−0.06*	0.107 ***3.66***	382	467	13	10	0
GICS partition most closely proxying how analysts cover (59 industries)	1.235 ***6.36***	1.77	0.49	1.291 ***6.55***	1.165 ***6.00***	−0.029 *−0.61*	−0.091 ***−2.01***	−0.039 *−0.65*	0.085 ***2.81***	374	456	16	42	0
Finest GICS partition (122 sub-industries)	0.997 ***5.48***	1.66	0.38	1.064 ***5.78***	0.946 ***5.22***	−0.034 *−0.76*	−0.091 ***−2.16***	−0.063 *−1.14*	0.080 ***2.83***	356	425	23	95	0
Panel B. Partitions Equal Weighted; Stocks Value Weighted; Various Degrees of Coarseness of the GICS-Code Partitions														
No partition: stocks equal weighted without regard for GICS code	0.182 *0.57*	2.90	−0.06	0.164 *0.50*	−0.061 *−0.19*	0.031 *0.40*	−0.026 *−0.35*	0.099 *1.00*	0.153 ***3.06***	374	456	0	1	0
Coarsest GICS partition (10 sectors)	0.360 ***1.71***	1.92	0.00	0.391 ***1.85***	0.357 *1.64*	−0.037 *−0.69*	−0.098 ***−1.93***	−0.006 *−0.09*	0.023 *0.67*	382	469	0	10	0
Finer GICS partition (23 industry groups)	0.771 ***4.09***	1.72	0.24	0.851 ***4.49***	0.753 ***3.96***	−0.064 *−1.36*	−0.086 ***−1.95***	−0.083 *−1.42*	0.067 ***2.25***	382	467	5	18	0
GICS partition most closely proxying how analysts cover (59 industries)	0.801 ***4.10***	1.78	0.25	0.886 ***4.68***	0.822 ***4.25***	−0.101 ***−2.12***	−0.115 ***−2.56***	−0.077 *−1.29*	0.044 *1.44*	374	456	10	48	0
Finest GICS partition (122 sub-industries)	0.750 ***4.00***	1.71	0.23	0.825 ***4.41***	0.796 ***4.13***	−0.078 *−1.64*	−0.098 ***−2.19***	−0.082 *−1.38*	0.020 *0.65*	356	425	20	98	0

Table 5 compares results for the recommendation long-short portfolios described in Section III.A for various degrees of coarseness of the GICS-code partitions. Panel A (or Panel B) shows percentage monthly returns (column 1), standard deviations (column 2), monthly Sharpe ratios (column 3), and estimates from time-series regressions of the calendar-time portfolios when stocks are equal weighted (or value weighted) within industry partitions. Column 4 shows the intercept from the Fama and French three-factor model. Columns 5–9 show estimates for the four-factor model. *t*-statistics (in italics) in bold indicate estimates that are significant at the 10% level. Columns 10 and 11 show the average number of stocks long and short per month. Column 12 shows the number of partition members with returns that are greater than ($\mu > 0$), equal to ($\mu = 0$), or less than ($\mu < 0$) zero at the 10% significance level over the time period.

FIGURE 2

Long Upgrade/Short Downgrade Portfolio Returns by Analyst Coverage and Company Size

Graph A



Graph B

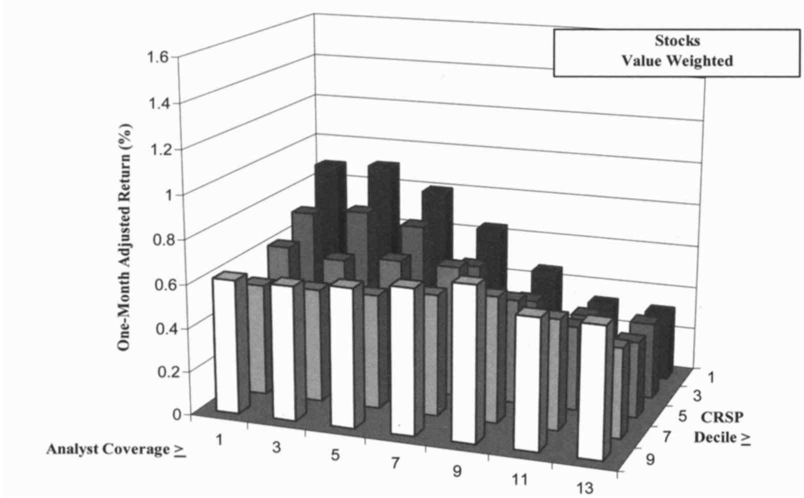


Figure 2 shows the percentage monthly adjusted returns from portfolios formed in the time period 1996 to 2002 using the long upgrade/short downgrade Changes Strategy defined in Section III.A. Portfolio returns in the graphs are chosen from stocks conditional on analyst coverage and CRSP NYSE size decile. Portfolios are equal weighted by industry. Within each industry portfolio, stocks are equal weighted (Graph A) or value weighted (Graph B). Adjusted returns are the intercepts from time-series regressions of portfolio one-month returns using the Fama and French three-factor model.

stricted to upgraded and downgraded stocks of companies with the greatest market capitalization (CRSP deciles 9 and 10) and substantial analyst coverage (13 or more analysts per stock), returns remain significantly positive for both equal- and value-weighted portfolios.

We conclude that, in aggregate, analysts' ability to distinguish stocks as relative winners or losers within their industries is substantial and economically significant. We emphasize that the returns documented are before transactions costs. It is also worth noting that we have done little to try to optimize a recommendation-based trading 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 (Green (2006) in this issue). Future research could examine the effects of more frequent rebalancing.[21]

Ivkovic and Jegadeesh (2004) suggest another area for possible optimization by documenting that price reactions to analyst recommendations generally increase with time from the last scheduled earnings announcement, consistent with analysts' ability to independently gather 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.[22] Therefore, Recommendation Changes portfolio strategies that condition or weight changes by proximity to earnings announcements might yield even better returns.

IV. Industry-Aggregated Analyst Recommendation Changes and Industry Price Momentum

A. Motivation

In Section III, we show that analysts' upgrades and downgrades can provide investment value for ranking future winner and loser stocks within industries. Section IV examines the linkages between recommendation upgrade/downgrade information, aggregated at the industry level, and industry returns. We address the following questions: i) Do industry returns exhibit price momentum when industries are classified according to Wall Street convention, i.e., using the GICS classifications? ii) Does analyst recommendation information, aggregated by industry, exhibit month-to-month momentum? iii) Do analysts chase or respond to industry price momentum in their recommendation changes?

We use GICS classifications to form monthly industry return series for each of the 59 industries. The GICS allows us to examine industry price momentum relative to analyst information flows according to industry classifications that investors incorporating Wall Street research would approximately use.

[21]The average one-month return for the second month following portfolio formation is also positive and statistically significant (0.36%). Returns for months beyond two months are not significant, however.

[22]See Conrad, Cornell, Landsman, and Rountree (2006) in this issue for an examination of analysts' upgrade and downgrade responses to public information releases as measured by large stock price changes.

To aggregate analyst information for each industry, we construct two industry recommendation measures:

The *Industry Recommendation Change Measure* is simply the equal-weighted average of the aggregate recommendation change measure (AgChange) for all the stocks in the industry. (In other words, AgChange, as defined in the previous section for the Recommendation Changes Strategy portfolios, is calculated for each stock, and the industry recommendation change measure is the mean for all the stocks in a given industry.) This measure will give greater emphasis to larger stocks, since more analysts typically follow larger stocks, and hence a disproportional number of changes will come from the larger stocks using this measure.

The *Industry Recommendation Change Measure (Coverage Adjusted)* is the same as for the Industry Recommendation Change Measure, except that AgChange for each stock is first divided by the number of analysts that cover the stock before calculating the average for the industry. This variation adjusts the data for the fact that more recommendations will be issued when there are more analysts following the stock. Hence, it will give a more equal-weighted emphasis to industry information.

We demonstrate the calculation of the industry recommendation change measures as follows. Suppose an industry consists of the following two companies: company A with two analysts covering it that month and company B with coverage by four analysts that month (per the IBES monthly recommendation summary data). If company A receives one upgrade in the month and company B receives two upgrades and one downgrade that month, then industry recommendation change measures are:

Industry Recommendation Change Measure

$$\begin{aligned} &= \text{AgChange}_{\text{CompanyA}} + \text{AgChange}_{\text{CompanyB}} \\ &= 1 + (2-1) \\ &= 2. \end{aligned}$$

Industry Recommendation Change Measure (Coverage Adjusted)

$$\begin{aligned} &= \frac{\text{AgChange}_{\text{Company A}}}{2\text{ analysts}} + \frac{\text{AgChange}_{\text{Company B}}}{4\text{ analysts}} \\ &= 1/2 + (2-1)/4 \\ &= 3/4. \end{aligned}$$

B. Results

First, we examine the GICS classification industry returns for evidence of price momentum. Table 6, Panel A provides results of Spearman rank tests for serial correlation of the industry one-month returns with monthly returns in each of the previous six months. Hou (2004) provides evidence that the industry price momentum anomaly results from the returns of larger firms within industries leading the returns of the smaller firms within the same industry. Hou also finds that, after controlling for size, returns of firms with more analyst coverage lead those with less coverage. Thus, Table 6, Panel A breaks stocks into three partitions by amount of analyst coverage. The partitions are stocks with coverage by one–four analysts, stocks with coverage by five–14 analysts, and stocks with coverage by 15 or more analysts. (Fifty percent of stocks in our dataset that have coverage by at least one analyst have the coverage of four or fewer analysts. The top 10% of stocks with the most analyst coverage are covered by 15 or more analysts.) Industry returns are also shown for an all-stock portfolio that consists of all stocks in the industry, including those without any analyst coverage.

TABLE 6

Serial Rank Correlations of Various Industry Returns and Industry Recommendation Measures

Month t	Month $t-1$	Month $t-2$	Month $t-3$	Month $t-4$	Month $t-5$	Month $t-6$
Panel A. Industry Returns						
Stocks covered by 1–4 analysts	**0.103*****	0.009	−0.006	0.011	0.037	0.017
Stocks covered by 5–14 analysts	0.042	−0.002	0.019	−0.010	0.009	0.017
Stocks covered by 15+ analysts	−0.009	0.033	0.022	−0.026	0.054*	0.063*
All stocks	**0.121*****	0.000	0.015	0.017	0.039	0.036
Panel B. Industry Recommendation Change Measure						
Stocks covered by 1–4 analysts	0.017	0.026*	0.017	0.027*	0.015	−0.003
Stocks covered by 5–14 analysts	**0.096*****	**0.058*****	**0.056*****	**0.040****	0.021	0.003
Stocks covered by 15+ analysts	**0.084*****	**0.078*****	0.032	**0.036****	−0.006	0.030*
All stocks covered by analysts	**0.140*****	**0.103*****	**0.078*****	**0.077*****	**0.054*****	**0.048*****

Table 6 shows Spearman rank correlation estimates for monthly industry returns (Panel A) and industry recommendation change variables (Panel B) as defined in Section IV.A. Correlation estimates are for each variable (Month t) with lagged values of itself for months $t-1$ through $t-6$. Industry variables are calculated for various partitions of analyst coverage (specifically stocks with 1–4 analysts, 5–14 analysts, or 15 or more analysts) per the IBES monthly summary recommendation file. For "All stocks" (Panel A), the industry return variable is calculated using all stocks in the industry, regardless of whether they receive any analyst coverage. For "All stocks covered by analysts" (Panel B), the industry recommendation change variable is calculated using all stocks in the industry that have the coverage of at least one analyst. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Coefficients for levels 5% and 1% are in bold.

The results in Table 6, Panel A show that industry returns for the all-stock portfolio and for the partition of stocks with least analyst coverage show evidence of serial correlation for one month ahead but not longer. Returns for stocks covered by more analysts (the five–14 analyst partition and the 15 plus partition) show virtually no serial correlation.[23]

Spearman rank tests for serial correlation of industry recommendation information are shown in Panel B of Table 6. The variable is the industry recommendation change measure, defined in Section IV.A.[24] We observe substantial evidence of industry momentum in the industry recommendation change information. In fact, the industry recommendation change measure shows serial correlation even six months out when recommendation information is aggregated across all stocks

[23]Moskowitz and Grinblatt (1999) find evidence of industry momentum using longer formation periods. Also, unlike the method of ranking industries based on one-month returns shown here, they use a longer return time frame when ranking industries. They use a different method for categorizing industries and a coarser partition. Also, it is worth noting that we include stocks in industry returns only if they receive the coverage of at least one analyst.

[24]The Spearman rank tests were conducted for both the industry recommendation change measure and the industry recommendation change measure (coverage adjusted) variables defined in Section IV.A. The results were qualitatively similar for the two variables. To save space, results are shown only for the first variable.

in the industry or aggregated across the stocks with the most analyst coverage. This is not the case for stocks covered by the fewest analysts, however. Recommendation information aggregated across the 50% of stocks with the lowest analyst coverage (i.e., one to four analysts) shows little evidence of persistence.

Table 7 shows Spearman rank correlation estimates when each industry return variable or industry recommendation variable (month t) is compared with a variable in the prior month (month $t-1$). We find that the industry returns of stocks covered by more analysts lead the returns of stocks with less analyst coverage in the same industry. The correlation estimate for the industry return of stocks covered by one–four analysts (month t) and the same-industry prior month return of stocks covered by 15 or more analysts (month $t-1$) is 0.100, which is significant at the 1% level. Conversely, the industry returns of stocks covered by 15 or more analysts show virtually no correlation with the prior month returns of the least covered stocks in the same industry (estimate = 0.019, not significantly different from zero). That is, there is a lead-lag relationship in one direction, namely from large stocks to small stocks, but not the other way around.

TABLE 7

Rank Correlations of Various Industry Returns and Industry Recommendation Measures

	Industry Returns				Recommendation Change Measure			
Month t \ *Month t − 1*	1–4 Analysts	5–14 Analysts	15 or More Analysts	All Stocks	1–4 Analysts	5–14 Analysts	15 or More Analysts	All Stocks with Coverage
Panel A. Industry Returns								
Stocks covered by 1–4 analysts	**0.103*** **	**0.130*** **	**0.100*** **	**0.138*** **	0.027*	0.017	−0.013	0.022
Stocks covered by 5–14 analysts	0.061*	0.042	**0.094*** **	0.063*	0.026*	−0.005	−0.014	0.009
Stocks covered by 15+ analysts	0.019	0.016	−0.009	0.025	0.008	−0.007	0.001	0.012
All stocks	**0.099*** **	**0.105*** **	**0.110*** **	**0.121*** **	**0.030** **	−0.002	−0.014	0.019
Panel B. Recommendation Change Measure								
Stocks covered by 1–4 analysts	**0.041** **	**0.050*** **	**0.046*** **	**0.047*** **	0.017	**0.064*** **	**0.062*** **	**0.079*** **
Stocks covered by 5–14 analysts	0.031*	**0.045*** **	**0.066*** **	**0.039** **	0.025	**0.096*** **	**0.045*** **	**0.091*** **
Stocks covered by 15+ analysts	0.026	**0.044** **	0.023	**0.044** **	**0.050*** **	**0.091*** **	**0.084*** **	**0.114*** **
All stocks covered by analysts	0.031*	**0.056*** **	**0.061*** **	**0.045** **	**0.039** **	**0.116*** **	**0.095*** **	**0.140*** **

Table 7 shows Spearman rank correlation estimates for monthly industry returns and industry recommendation change variables as defined in Section IV.A. Correlation estimates are for each variable compared with a variable in the prior month. Industry variables are calculated for various partitions of analyst coverage (specifically stocks with 1–4 analysts, 5–14 analysts, or 15 or more analysts) per the IBES monthly summary recommendation file. For "All Stocks," the industry return variable is calculated using all stocks in the industry, regardless of whether they receive any analyst coverage. For "All stocks covered by analysts," the industry recommendation change variable is calculated using all stocks in the industry that have the coverage of at least one analyst. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Coefficients for levels 5% and 1% are in bold.

The results in Table 7 (as well as in other analysis not reported) suggest little (and then only short-term) value from using analyst recommendation information, aggregated by industry, for identifying profitable or informative industry rotation strategies. Specifically, only the all-stock industry returns (month t) and the prior-month Industry Recommendation Change Measure for stocks with one to four analysts covering (month $t-1$) have a correlation coefficient that is significant at the 10% level. In the opposite direction, some of the analysts' collective information measures are correlated with industry returns in the prior month. Jegadeesh, Kim, Krische, and Lee (2004) conclude that analysts may be influenced by the characteristics of individual stocks, such as glamour versus value and price momentum. Table 7 shows that analysts' recommendations appear to be influenced by recent abnormal industry performance as well. That is, analysts' recommendation changes in an industry seem to follow abnormal performance within that industry.

To further examine the possible investment value of industry-aggregated analyst recommendations for forecasting hot and cold industries, we construct long-short portfolios using each of the two industry recommendation measures (i.e., the industry recommendation change measure and the industry recommendation change measure (coverage adjusted)). Portfolios purchase stocks in industries that have a positive value for the industry measure that month (i.e., net upgraded industries) and sell short stocks in industries that have a negative value (i.e., net downgraded industries). Industries are equal weighted in the long and short portfolios, and stocks within industries are equal weighted. Stocks are included in industry portfolios only if they have the coverage of at least one analyst that month. Industries are chosen for portfolios using information at the end of month $t-1$. We then calculate the one-month holding period return for month t. Neither the means of the monthly post-formation raw return time series nor the intercepts from three- and four-factor regressions are significant at the 10% level for either of the two measures. We conclude that industry-aggregated analyst recommendation information is not useful for predicting future relative underperforming or outperforming industries in any meaningful, incremental way.

V. Conclusions

Virtually all Wall Street (sell-side) analysts take an industry perspective in coming up with the valuations, including earnings estimates and recommendations, which they provide to investors. We show that analyst upgrade and downgrade information, aggregated within industries and across industries, enhances our understanding of market efficiency and price momentum in several ways. First, recommendation upgrades and downgrades, aggregated across all analysts for stocks within each industry, provide a much better signal of future returns than does the standard non-industry approach. The signal to noise ratio, as measured by the Sharpe ratio, is almost doubled versus the non-industry approach, and is several times that of the typical price momentum strategies. We conclude that recommendation information is quite valuable for identifying short-term within-industry mispricings, but this same information, aggregated by industry, is not of obvious value in projecting future relative returns across industries. Our results are consistent with the characterization of analysts as good stock pickers within their industry of expertise, but not as useful sector rotation prognosticators.

Our findings also suggest some important implications for future measurements and comparisons of analysts' research. Previous research documents the importance of controlling for stock characteristics (Jegadeesh, Kim, Krische, and Lee (2004)), company size (Womack (1996)), and degree of analyst competition (Hong, Lim, and Stein (2000)). Our findings suggest that comparisons or measurements also should control for the industry the analyst covers. Perhaps more importantly, comparisons across research firms should control for the degree to which the research coverage is diversified across industries. For example, we have documented that the 20 largest brokerage firms provide recommendations in almost all industries while many other boutique firms provide coverage of only a few industries. Our findings suggest that, if compared on the basis of the mean-variance of returns, all else equal, the aggregate recommendations of any firm that provides research coverage that is widely diversified across industries should be expected to outperform those of any firm that covers only a few industries.

APPENDIX
Industry Group Statistics

	GICS Industry Code	GICS Industry Name	No. of Companies	Analyst Covered % of Total	Mean Return	Monthly Sharpe Ratio	Stocks Long	Stocks Short
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1	101010	Energy Equipment & Services	115	87.0%	0.76%	0.07	9.6	10.1
2	101020	Oil & Gas	285	68.1%	**1.11%**	0.17	15.7	17.1
3	151010	Chemicals	163	73.0%	**1.08%**	0.13	7.7	9.3
4	151020	Construction Materials	35	68.6%	−1.08%	−0.13	1.5	1.7
5	151030	Containers & Packaging	66	71.2%	0.76%	0.04	3.0	3.1
6	151040	Metals & Mining	197	60.9%	0.86%	0.06	8.3	10.0
7	151050	Paper & Forest Products	54	70.4%	**1.74%**	0.20	4.1	4.0
8	201010	Aerospace & Defense	107	74.8%	1.29%	0.11	4.3	5.2
9	201020	Building Products	68	60.3%	2.79%	0.18	2.1	2.8
10	201030	Construction & Engineering	66	65.2%	1.71%	0.11	2.1	2.2
11	201040	Electrical Equipment	127	74.0%	0.63%	0.02	3.8	4.6
12	201050	Industrial Conglomerates	18	83.3%	0.18%	−0.01	1.3	1.6
13	201060	Machinery	233	69.5%	0.09%	−0.05	8.0	10.0
14	201070	Trading Companies & Distrib	17	70.6%	1.72%	0.11	1.2	1.8
15	202010	Commercial Svcs & Supplies	542	69.0%	1.20%	0.12	14.6	19.3
16	203010	Air Freight & Couriers	30	83.3%	**2.45%**	0.18	2.6	3.0
17	203020	Airlines	41	87.8%	**2.52%**	0.21	3.4	4.3
18	203030	Marine	14	57.1%	—	—	—	—
19	203040	Road & Rail	87	79.3%	1.52%	0.14	4.2	4.8
20	203050	Trans Infrastructure	9	44.4%	—	—	—	—
21	251010	Auto Components	115	69.6%	0.28%	−0.01	4.0	5.4
22	251020	Automobiles	24	95.8%	1.64%	0.11	2.1	2.3
23	252010	Household Durables	190	75.3%	**2.10%**	0.26	7.0	8.7
24	252020	Leisure Equipment & Products	98	71.4%	**2.52%**	0.18	2.3	3.4
25	252030	Textiles & Apparel	154	72.1%	**2.25%**	0.22	5.0	6.3
26	253010	Hotels Restaurants & Leisure	289	72.0%	**1.08%**	0.17	11.3	13.8
27	254010	Media	369	71.5%	0.71%	0.07	12.2	14.9
28	255010	Distributors	79	51.9%	3.05%	0.11	1.6	1.9
29	255020	Internet & Catalog Retail	95	85.3%	1.81%	0.08	2.5	2.9
30	255030	Multiline Retail	56	87.5%	0.86%	0.06	4.8	5.2
31	255040	Specialty Retail	244	81.6%	1.03%	0.11	15.6	17.8
32	301010	Food & Drug Retailing	102	78.4%	0.22%	−0.02	4.2	4.9
33	302010	Beverages	47	78.7%	**2.26%**	0.21	3.0	3.2
34	302020	Food Products	149	75.2%	**1.54%**	0.20	7.2	8.5
35	302030	Tobacco	19	84.2%	2.59%	0.20	1.4	1.9
36	303010	Household Products	18	77.8%	−0.95%	−0.13	1.8	1.9
37	303020	Personal Products	53	58.5%	3.69%	0.19	1.7	2.0
38	351010	Health Care Equipment & Supp	384	76.6%	0.75%	0.04	10.1	12.9
39	351020	Health Care Providers & Svcs	344	78.8%	0.76%	0.06	13.9	16.4
40	352010	Biotechnology	301	75.1%	0.46%	0.01	7.1	9.6
41	352020	Pharmaceuticals	189	79.4%	0.93%	0.08	7.6	8.4
42	401010	Banks	1,224	67.7%	**1.20%**	0.37	30.6	38.7
43	402010	Diversified Financials	290	72.4%	0.35%	0.00	9.6	13.0
44	403010	Insurance	282	80.9%	0.06%	−0.06	12.7	16.4
45	404010	Real Estate	278	71.2%	**0.76%**	0.12	8.8	14.6
46	451010	Internet Software & Services	464	79.5%	**3.35%**	0.17	7.8	9.2
47	451020	IT Consulting & Services	147	81.0%	1.11%	0.08	5.3	6.3
48	451030	Software	592	80.7%	0.80%	0.06	18.7	23.0
49	452010	Communications Equipment	305	80.7%	1.30%	0.09	12.1	14.3
50	452020	Computers & Peripherals	205	70.7%	**2.10%**	0.18	7.6	8.9
51	452030	Electronic Equip & Instru	294	68.0%	1.57%	0.14	10.0	12.9
52	452040	Office Electronics	16	81.3%	2.53%	0.19	1.2	1.3
53	452050	Semiconductor Equip & Prods	252	86.5%	1.29%	0.12	16.3	20.2
54	501010	Diversified Telecomm Svcs	204	76.5%	−0.10%	−0.04	7.9	9.4
55	501020	Wireless Telecomm Svcs	90	83.3%	0.28%	−0.01	3.2	3.8
56	551010	Electric Utilities	114	92.1%	**1.12%**	0.19	9.0	9.1
57	551020	Gas Utilities	63	79.4%	0.37%	0.00	3.0	3.7
58	551030	Multi-Utilities	34	88.2%	1.83%	0.09	2.9	3.3
59	551040	Water Utilities	22	86.4%	3.97%	0.39	1.3	1.3
		All	10,469	74.4%				
		Mean	177	75.3%				
		Min	9	44.4%				
		Max	1,224	95.8%				

The Appendix reports statistics for the 59 S&P/MSCI GICS industries. Columns 1 and 2 list the code number and industry name assigned by the S&P/MSCI Global Industry Classification Standard. Column 3 shows the number of companies in the industry. Column 4 shows the percentage of companies covered by at least one analyst. Column 5 reports time-series statistics for the monthly returns from individual industry portfolios that are created using the Recommendation Changes Strategy defined in Section III.A. Each month, 57 portfolios, each limited to the stocks in its industry classification, are formed using the long upgrade/short downgrade strategy. Stocks are equal weighted in the long and short portfolios. (Two industries, specifically those with GICS codes 203030 and 203050, are excluded because they have upgrades and downgrades only for a few months during the 1996–2002 time period.) Percentage monthly returns (column 5) in bold are significant at the 10% level. Monthly Sharpe ratios are reported in column 6. Columns 7 and 8 show the average number of stocks long and short per month.

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