# Analysts' Industry Expertise

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**Abstract**

Industry expertise is an important aspect of sell-side research. We explore this aspect using a novel dataset of industry recommendations, which are often issued by strategy analysts. We study sell-side analysts' ability to rank industries relative to each other (across-industry expertise), and how it relates to analysts' ability to rank firms in a particular industry (within-industry expertise). We find that analysts express more optimism towards industries with higher levels of investment, past profitability, and past returns. Analysts exhibit across-industry expertise, as portfolios based on industry recommendations generate abnormal returns over both short and long horizons, beyond what would be explained by industry momentum. Additionally, industry recommendations contain information, which is orthogonal to the information revealed in firm recommendations, and more so for brokers who benchmark their firm recommendations to industry peers. Consequently, the investment value of sell-side analysts' recommendations is enhanced when both dimensions of industry expertise are utilized by considering industry and firm recommendations in combination.

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# 1 Introduction

Industry knowledge in sell-side research is highly valued by investors. For example, *Institutional Investor Magazine* has been surveying institutional investors on the importance of various attributes in sell-side research analysts. For each year in the period 1998-2010 industry knowledge was deemed the most important research attribute of equity analysts.[1] Indeed, industry analysis is an important component of the sell-side research business. First, strategy analysts in brokerage houses (strategists for short) often issue industry-level forecasts and recommendations in their periodic reports. These analysts typically follow a top-down approach, trying to exploit sector-rotation strategies mostly driven by the cyclicality of different industries and their sensitivities to macroeconomic shocks. Second, firm-level analysts, who constitute the vast majority of the sell-side research personnel, specialize by industry. They typically work in groups covering a set of firms that are similar to each other in their industry characteristics. At the firm level, they analyze specific firms in their assigned industry, providing earnings estimates, recommendations, price targets, etc. At the industry level, they write periodic industry reports, mostly from a bottom-up perspective, and often incorporate into their reports the industry recommendation advice from the strategists. The extant literature has explored analysts' firm recommendations extensively.[2] Despite the importance of industry expertise in sell-side research, this topic has not yet been fully investigated, probably due to the lack of large scale data on industry recommendations.

Industry expertise can take two forms. The first is *within-industry* expertise, which reflects the analyst's knowledge of economic factors affecting the performance of firms in the industry, and the analyst's ability to value and rank firms in the industry. The second form is *across-industry* expertise, which reflects the ability to compare the prospects of the industry to the market and to other industries. Explicit industry recommendations should reflect across-industry expertise. By contrast, firm recommendations can reflect both within- and across-industry expertise. Boni and Womack (2006) focus mostly on analysts' within-industry expertise as reflected in firm recommendations. In this paper we study whether sell-side analysts possess

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[1] See http://www.institutionalinvestor.com/Research/961/What-Investors-Really-Want.html for the most recent edition (2010) of the ranking of the research attributes valued by investors.

[2] For a recent review of the literature see Ramnath, Rock, and Shane (2008).

across-industry expertise as reflected in their industry recommendations, and how the within- and across-industry expertise interact.[3]

To motivate the analysis, consider the following example. During the second half of 2007, the median firm recommendation issued for both GM and Chevron was a ‘hold.’ However, at that time, analysts issued bearish recommendations for the Automobiles industry as a whole, while they typically issued bullish recommendations for the Oil industry. This scenario raises several interesting questions.

First, what are the industry attributes that determine the level of industry recommendations? In the example above, did strategists favor the energy industry because it had shown high past returns, high profitability, or perhaps high equity issuance volume? It may also be that macroeconomic conditions such as the slowdown in the economy during that time period led strategists to favor the Oil industry over the Automobiles industry. Second, do analysts have across-industry expertise as reflected in their industry recommendations? In particular, do recommendations for industries carry any value to investors?

Third, to the extent that industry recommendations do reflect across-industry insights, is this information incremental to that already included in firm recommendations? Indeed, firm recommendations can include information about the ranking of firms within an industry, and about the performance of firms (or the industry to which they belong) relative to the market as a whole. Thus, it is possible that industry recommendations are subsumed by firm recommendations or their aggregations. Finally, a closely related question is whether firm-level analysts benchmark their *firm* recommendations to the market or to industry peers. In the example above, it is interesting to understand whether the ‘hold’ recommendations assigned to GM and Chevron have the same meaning or whether they should take into account the different industry recommendations. In this sense we ought to understand whether the “hold” recommendation issued to GM was relative to the entire market or, instead, relative to peers such as Ford, Chrysler, and Toyota.

To answer these questions we use the IBES database to collect industry recommendations. When an analyst produces a report with a recommendation on a firm’s stock, she often includes in the report the brokerage house’s current outlook on that firm’s industry. In

[3] Throughout the paper, the terms “sell-side analysts,” or simply “analysts,” refer to both firm-level and strategy analysts. Occasionally, when the distinction is important we refer to each type of analyst specifically.

September 2002, IBES started recording the textual information on the industry outlook for those brokers reporting the industry recommendation in their firm reports.

We identify 33 financial institutions for which textual information on industry outlooks is available. Our sample includes a total of 41,315 industry recommendations in the period from September 2002 through December 2009. Overall, 32% of the industry recommendations are optimistic, 54% are neutral, and 14% are pessimistic. We study the factors associated with the level of optimism in industry recommendations. We find that past profitability, past returns, and the extent of R&D and Capex activity are positively associated with the probability of issuing an optimistic industry recommendation. We also find that analysts indeed exploit sector rotation strategies as they are less optimistic toward cyclical industries during recessions.

We next turn to examine the across-industry expertise of analysts as reflected in industry recommendations. These industry recommendations are for the most part determined by strategists using a macroeconomic point of view. Strategists also rely on the input and knowledge of firm-level analysts, who can aggregate information from their analysis of individual firms. It is thus possible that industry recommendations can identify "hot" and "cold" industries, reflecting the joint knowledge of strategists and firm-level analysts. On the other hand, several reasons conspire to make it difficult for investors to exploit analysts' across-industry expertise. One of the reasons relates to analysts' role in collecting and using information. The literature has covered extensively how firm-level analysts' special access and relationships with the firm affect the way they perform.[4] These attributes are likely to augment analysts' within-industry expertise. However, it is not clear whether analogous attributes can be developed with respect to the analysis of macroeconomic data, which is key in generating industry recommendations. Another issue that may limit our ability to find evidence of across-industry expertise is that industry recommendations are likely to be quite stale when they become available on IBES. The industry recommendations that we observe are recorded only when a new firm recommendation is issued, so we cannot identify the exact date in which the industry recommendation was originally issued.

[4] For example, the presence of an underwriting relationship enables a broker to issue better earnings forecasts [Malloy (2005)] or to be a better market maker [Ellis, Michaely and O'Hara (2000); Madureira and Underwood (2008)], while the presence of a lending relationship affects the ability of a broker to secure future underwriting business [Drucker and Puri (2005); Ljungqvist, Marston, and Wilhelm (2006)], get better terms for new security offerings [Puri (1996)], or provide better earnings forecasts [Ergungor, Madureira, Nayar, and Sing (2008)].

Our approach to testing for the presence of industry expertise is to examine whether investors can obtain abnormal return by following these recommendations. This approach is similar to prior studies focusing on the investment value of firm recommendations (e.g., Barber et al, 2001, 2006; Boni and Womack, 2006). Specifically, we compute abnormal returns of industry portfolios formed based on changes (upgrades/downgrades) in monthly average industry recommendations.[5] We find that a portfolio of industries about which analysts are most optimistic carries a significant abnormal return of 0.6% per month, while a pessimistic portfolio carries a significantly negative abnormal return of 0.9% per month. These results suggest the presence of across-industry expertise reflected in both optimistic and pessimistic industry recommendations. The abnormal returns are strongest for short horizons of one month. Their magnitudes and statistical significance diminish over longer horizons of up to 12 months, but we do not observe a complete reversal. Additionally, the results do not appear to be driven by an "up" or "down" market, and are not reversed during the bear market of 2008.

Next we turn to studying the interaction between across- and within-industry expertise of analysts. In particular, we attempt to find whether the across-industry expertise of analysts is already reflected in firm recommendations, or in their aggregations. To this end, it is important to identify whether firm recommendations contain information regarding industry outlooks, or whether firm recommendations just rank firms within industries. Our first step is to examine brokers' disclosures about how their firm recommendations should be interpreted. By examining these disclosures for the 20 largest brokers, we find that 10 of these brokers, including six in our industry recommendation sample, benchmark their firm recommendations to industry peers, while the other 10 rely on a market benchmark.

Different benchmarks imply different ways by which firm recommendations reflect industry information. If brokers use an industry benchmark, then their firm recommendations will contain no industry-wide information. Essentially such brokers limit their firm recommendations to ranking firms within industries, and only their within-industry expertise gets reflected in the recommendations. By contrast, if brokers use a market benchmark, then their firm recommendations are expected to incorporate industry outlooks and to reflect both within-industry and across-industry expertise. To help us distinguish between these alternatives we construct "pseudo industry recommendations" – similar to those used in Boni and Womack

[5] Our measures of abnormal returns are in-sample and out-of-sample versions of the Fama-French four factor alpha.

(2006) – by value weighting all firm recommendations that belong to a specific GICS industry. Interestingly, we find that the correlation between the pseudo industry recommendations and the true industry recommendations is low (around 0.10-0.15), suggesting that the two are based on different information. We then repeat the abnormal return analysis using the pseudo industry recommendations. As expected, we find some evidence of abnormal returns for brokers who benchmark their firm recommendation to the market. By contrast, pseudo industry recommendations by brokers who benchmark their firm recommendations to industry peers generate no abnormal returns. Hence, at least for analysts who benchmark firm recommendations to industry peers, it appears that true industry recommendations contain information regarding industry outlooks which is not already reflected in firm recommendations or in aggregations thereof.

Prior research demonstrates that firm recommendations carry investment value.[6] If indeed firm recommendations are often aimed at ranking firms within industries, then adding the across-industry information by conditioning firm recommendations on the prospects of the relevant industry should increase their investment value. Our next set of tests pursues this line of thought by combining both analysts' across- and within-industry expertise in forming investment portfolios. At the industry level, we classify industries into three portfolios based on true industry recommendations as before. At the firm level, we follow Boni and Womack (2006) and classify firms into net upgraded and net downgraded firms. A firm can be allocated to one of six portfolios depending on its own recommendation (upgraded/downgraded) and on whether its industry carries an optimistic, neutral or pessimistic prospect.

The results support the idea that across- and within-industry expertise complement each other. Indeed, combining industry and firm recommendations adds investment value over investment horizons of up to 12 months. For example, when considering a short investment horizon of one month, net upgraded stocks have abnormal returns only if they are part of industries with an optimistic or neutral outlook, but not when they are part of industries with pessimistic outlooks. In a similar fashion, net downgraded stocks have significantly negative alphas only when they belong to industries downgraded to a pessimistic outlook. In fact, when a downgraded firm belongs to an upgraded industry, it generates a *positive* abnormal return.

[6] See for example Stickel (1995); Womack (1996); Barber, Lehavy, McNichols, and Trueman (2001, 2006); Jegadeesh, Kim, Krische and Lee (2004); and Barber, Lehavy, and Trueman (2010).

Finally, we find that portfolios that are based on the combined signal of both industry and firm recommendations outperform portfolios based on just one of the two signals.

The results so far are consistent with analysts possessing across-industry expertise. However, two other explanations also seem plausible. First, it is possible that analysts do not possess any across-industry expertise. Instead, analysts chase industry momentum, and the abnormal returns we document are a reflection of this well-documented phenomenon [Moskowitz and Grinblatt (1999)]. We conduct multiple tests to explore this possibility. For instance, we consider portfolios based on industry recommendations after excluding industries that also exhibit momentum. The results show that industry recommendations have investment value regardless of past returns, supporting the idea that they reflect across-industry expertise.

Second, it may be that analysts do not possess insights regarding the long-term fundamentals of the industry. Rather, industry recommendations generate a "hype" or sentiment for some industries that leads to temporary price pressure and to the abnormal returns we observe. If that is the case, then the returns following industry recommendations should be short lived, as prices revert to fundamentals in the long-run. Consequently, a way to distinguish between this alternative explanation and the "industry expertise" hypothesis is to test whether the short-term abnormal returns obtained from following industry recommendations are reversed within one year. While the medium- to long-term returns (over horizons of up to 12 months) to following industry recommendations are lower than the corresponding one-month returns, they are often still significant. Moreover, a direct test does not show evidence of reversals. We conclude that to the extent that a reversal in returns exists, it is only partial. This is again consistent with analysts possessing across-industry expertise.

Our paper contributes to the literature in several ways. To our knowledge, this is the first paper to analyze the outputs of strategy analysts in the form of industry recommendations. These recommendations typically reflect a top-down approach and are thus very different from the firm-level recommendations studied in the existing literature. We also highlight the two dimensions of industry expertise (across-industry and within-industry) that could potentially be reflected in sell-side analysts' recommendations. Boni and Womack (2006) were the first to analyze the within-industry dimension. They show that the value of *firm* recommendations comes mostly from ranking firms within industries. Boni and Womack (2006) did not have access to industry recommendations, and instead analyzed aggregations of firm recommendations to assess across-industry expertise. They conclude that such aggregations cannot be used as signals for industry prospects. We extend the literature by directly testing for analysts' across-industry expertise using industry recommendation data. Our results suggest that analysts do possess across-industry expertise, and show the relevance of industry recommendations from an investment perspective. It is worth emphasizing that our study and Boni and Womack (2006) are not directly comparable since the sample periods are different. While Boni and Womack (2006) use data from 1996-2002, our data starts in September 2002.

Second, the paper also sheds new light on the information contained in firm recommendations. Different brokers define their firm recommendations based on different benchmarks – either the market or the peers in the industry. We establish that industry recommendations contain information that is reflecting analysts' across-industry expertise and that is orthogonal to the information included in firm recommendations, which mostly reflects within-industry expertise. In fact, firm recommendations are best interpreted in conjunction with industry recommendations, jointly exploiting both dimensions of expertise.

Finally, we revisit the unsettled issue of whether aggregations of firm recommendations at the industry level can serve as proxies for industry outlook. While Boni and Womack (2006) conclude that such aggregations are not good proxies for the industry prospects, Howe, Unlu, and Yan (2009) find modest evidence that they can forecast industry returns. We point out that industry aggregations of firm recommendations should reflect across-industry expertise conditional on the recommendation benchmark adopted by the broker. Accordingly, we show that aggregations of firm recommendations contain some information about the industry's prospects when issued by analysts using a market benchmark, but not when issued by analysts using the industry peers as a benchmark.

Thus, the paper highlights the role of analysts as producers of, or at least conduits for, information at the industry level. Piotroski and Roulstone's (2004) results using stock non-synchronicity measures imply that analyst activity – proxied by the number of analysts issuing forecasts for a firm – helps in incorporating industry information into market prices. Our study provides direct evidence for the presence of analysts' industry expertise. In particular, we study the previously unexplored across-industry dimension of analysts' expertise, and how it gets reflected in firm and industry recommendations.[7]

The rest of the paper proceeds as follows. In Section 2 we describe the data and in Section 3 we explore the determinants of industry recommendations. In Section 4 we study the across-industry expertise in sell-side research. Section 5 discusses the relation between across-industry and within-industry expertise. Section 6 explores two alternative explanations for the results. Section 7 concludes.

# 2 Data

## *2.1 Firm Analysts vs. Strategists*[8]

The bulk of the data employed in sell-side research studies concerns firm-level analysts. These analysts specialize by industry and produce earnings forecasts, price targets and firm recommendations. The production and dissemination of industry recommendations often involve the participation of a different type of sell-side analyst: the one working in the equity strategy group (strategist) of the brokerage house. Contrary to the traditional (firm-level) analysts, strategists are not linked to specific firms or industries, but rather focus on the equity market as a whole.

When strategists issue industry recommendations, they mostly rely on a top-down approach in which they analyze macroeconomic conditions. A common method for these strategists is to exploit "sector rotation" in which they follow business cycles and base industry recommendations on their estimates of the exposure of each industry to macroeconomic shocks. Strategists also often use as input information from firm-level analysts, who rely on a bottom-up approach.  Thus, industry recommendations are determined for the most part by strategists with the level of involvement of firm-level analysts varying from broker to broker. In some situations, e.g., when advice from strategists is not available, firm-level analysts can issue industry recommendations. Several brokers include their industry recommendations in periodic economic outlook reports published by the strategy department of the brokerage house. These

[7] Our paper also relates to the literature exploring the relative importance of industry selection in the investment process. See, for example, Froot and Teo (2008), Busse and Tong (2008), Kacperczyk, Sialm and Zheng (2005), and Avramov and Wermers (2006). Our results add to this literature by directly showing that industry specialists are capable of providing useful industry outlooks.

[8] We thank the reviewer for drawing our attention to the role of strategy analysts in the issuance of industry recommendations.

recommendations are also often incorporated into firm and industry reports that are produced by firm-level analysts. In particular, the data we use consists of industry recommendations that are attached to firm reports.[9,10]

The importance of the activities of strategy analysts is highlighted by the All-America Research Team (the "all-star") rankings from Institutional Investor (II) Magazine. Besides the traditional prizes for best analysts in each industry, II Magazine also grants awards for analysts under coarser categories such as Portfolio Strategy and Quantitative Research. These awards are sometimes given based on industry recommendations.[11]

### *2.2 Brokers and Industry Recommendations*

Starting in September of 2002 IBES began to record industry recommendations alongside firm recommendations.[12] This information is recorded in the 'btext' (more lately 'etext') field in the IBES recommendation file. This field always contains the text of the firm recommendation (e.g. 'buy', 'hold', 'underperform'). For investment banks that include an industry recommendation in their firm reports, the field also records the industry recommendations. See Appendix I for details.

In the period starting in September 2002 through December 2009, 33 brokers have provided at least one industry recommendation.[13] Panel A of Table 1 lists those brokers along with some information regarding their coverage. As listed, the six largest brokers in our sample in terms of the number of industry recommendations made available on IBES are Goldman Sachs, CSFB, Morgan Stanley, Bear Stearns, Lehman Brothers. (replaced by Barclays in 2008)

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[9] The information in this paragraph is based on interviews we conducted with current and former analysts (including strategists) from various brokerage houses including Goldman Sachs, JP Morgan, Morgan Stanley, Merrill Lynch, Robert Baird, Barclays (formerly Lehman Brothers), CSFB, UBS, Bear Stearns, and Sanford Bernstein.

[10] Strategists can also produce more aggregated data such as top-down earnings forecasts for the S&P 500 and the Dow Jones Industrial Average. See Darrough and Russell (2002).

[11] The qualitative descriptions of the analysts earning the all-star designations, both for the best analyst in each sector and for the best strategist, often draw attention to their correct calls on industry outlooks. For example, the II Magazine once emphasized how a first-prize industry analyst "had been urging clients to underweight their holdings in his sector" (2010 edition, page 47), while for the first-prize in the Portfolio Strategy category the II Magazine cherished the strategist call to "dump defensive stocks such as telecommunications and health care companies and load up on consumer discretionary stocks" (2009 edition, page 98) or how the strategist "reiterated his overweight stance" in a specific sector (2008 edition, page 98) that later outperformed the market.

[12] Note that IBES files starting from 2009 do not include recommendations from Lehman Brothers (before they were converted to Barclays). We obtain these recommendations from the 2008 files.

[13] In line with Kadan, Madureira, Wang, and Zach (2009) we omit from the sample recommendations re-issued during the change in rating systems during 2002. Similarly, we omit recommendations originally issued by Lehman Brothers, and then re-issued by Barclays when taking over Lehman's research department during 2008. That is, we only account for these recommendations once, when they were initially issued.

and CIBC. For these brokers, we find that industry recommendations are attached to firm recommendations over 95% of the time.

Two points should be noted. First, other large investment banks also issue industry recommendations. However, these banks do not include their industry recommendations in firm reports, and hence their industry recommendations are not recorded by IBES. In general, 16.6% of all firm recommendations in IBES during our sample period carry with them an industry recommendation. Second, 96% of all industry recommendations in our sample are issued by the seven largest brokers. Therefore, our conclusions mostly apply to the largest, full-service brokers.

*<Insert Table 1 here>*

### *2.3 Industry Classification*

IBES reports the industry recommendation issued by a broker for the industry to which a firm belongs. However, IBES does not explicitly report the industry to which the firm belongs, as defined by the broker. We infer this industry from the identity of the firm and its industry classification as defined by the General Industry Classification Standard (GICS) obtained from Compustat. This classification is maintained by Standard & Poor's and MSCI Barra, and is widely adopted by investment banks as an industry classification system (as opposed to the SIC classification that is popular among academics). The GICS system has four classification levels: 10 sectors, 24 industry groups, 68 industries, and 154 sub-industries.[14] These classifications are highly intuitive, and have been shown to better explain stock comovements compared to other popular industry classifications [Bhojraj, Lee, and Oler (2003)]. In the context of this research, Boni and Womack (2006) show that the GICS classification is a good proxy for how sell-side analysts specialize by industry.[15]

Similar to Boni and Womack (2006) and Bhojraj, Lee, and Oler (2003), we focus on the industry level (6 digits). Appendix II presents the complete list of industries using the GICS classification, as well as some basic statistics of industry coverage by the brokers in our

[14] Standard and Poors and MSCI Barra change their GICS industry definitions from time to time. The numbers listed here are as of August 2008, and have not changed until the end of the sample period.

[15] We extend the analysis offered in Boni and Womack (2006), by comparing the analyst coverage choice in our sample relative to different industry classifications: besides GICS, we also look at SIC (2 digits), IBES internal classification and the Fama-French 48 industries. The comparison (available upon request) shows that the GICS partition most closely resembles how brokers define their industries.

sample.[16] By casually examining industry classifications in the relevant investment banks, we find our classification to be broadly as fine as or finer than the one used by them. This ensures that our industry classification captures variations in industry recommendations within each broker.

According to Boni and Womack (2006), the percentage of all companies an analyst covers that are in one GICS industry averages 81% for analysts at the 20 largest brokerages. For our sample of brokers with industry recommendations, the statistic for the period 2002-2009 is 78%. This suggests that by relying on the GICS classification we are misclassifying industries relative to the true classification used by the broker about 22% of the time.[17] Note that such misclassifications work against finding any evidence of return predictability based on industry recommendations. In Section 4.1 we construct industry consensus recommendations in a way that mitigates some of the errors due to these inevitable misclassifications.

### *2.4 Industry Recommendations*

Similar to firm recommendations, brokerage houses use a variety of terms to express optimism, neutrality, or pessimism toward industries. In the case of firm recommendations, IBES transforms the textual recommendation into a five-point rating system (recorded in the IRECCD item). By contrast, the text of industry recommendation is not recorded numerically. Hence, we convert the text using a key presented in Appendix I. We code recommendations with an optimistic tone as '1', recommendations with a neutral tone as '2', and recommendations with a pessimistic tone as '3'. Thus, for each IBES entry that also includes the textual description of the industry outlook, we have both the recommendation for the firm itself (optimistic, neutral, or pessimistic) and the recommendation for the industry to which the firm belongs (again, optimistic, neutral, or pessimistic).

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[16] Notice that two of the GICS industries have been discontinued during our sample period. This is the reason why Panel A of Table 1 shows 70 industries with industry recommendations for Goldman Sachs and Morgan Stanley, while the number of GICS industries as of August 2008 is only 68.

[17] In fact, these numbers serve as an upper bound on the error, since in many cases analysts still use the GICS classification method, but occasionally focus on the industry-group or sector level, rather than the industry level. For example, an analyst can cover all firms in the 'Utilities' industry, while the GICS industry level distinguishes between 'Gas' and 'Electric Utilities'. Our method of constructing portfolios (see Section 4.1) is robust to such cases. Real errors can occur only when broker uses a classification system that is different from GICS.

## 3 Basic Characteristics of Industry Recommendations

Panels B through D of Table 1 present summary statistics to describe coverage and distributional properties of industry recommendations for the largest six brokers in our sample.[18] Panel B shows that coverage is quite comprehensive across the universe of industries for five out of the six brokers during 2002-2009.[19] This suggests that in contrast to firm recommendations, selection bias [McNichols and O'Brien (1997)] is not a major issue with industry recommendations for large brokers. Selection bias may, however, still be an issue for small brokers that focus on select industries.

Panel C presents the distribution of industry recommendations by year for all brokers in our sample. The table shows that the frequency of optimistic recommendations hovers around 30%, with little variation over the years. There is, however, a modest increase in the frequency of neutral recommendations accompanied by a decrease in the proportion of pessimistic recommendations. Panel D presents the average industry recommendations by broker for the six largest brokers during our sample period. The results show that there is little difference between the different brokers, as average recommendations hover somewhat below '2' (neutral to slightly optimistic) for all of them. These results suggest that brokers issue a pretty balanced distribution of industry recommendations, with just a small inclination toward optimism. In Section 5 we compare this distribution to that of the associated firm recommendations.

To better understand the determinants of industry recommendations we examine the probability of issuing an optimistic/pessimistic industry recommendation as a function of several factors. The main explanatory variables we investigate are industry size (aggregate market-value of all firms in the industry in the month before the recommendation), lagged industry and market returns, and industry value-weighted averages of market-to-book ratio, profitability (return on assets), R&D (as a fraction of assets), and capital expenditures (as a fraction of assets). All accounting variables are measured during the year prior to the issuance of the industry recommendation.

Given that industry recommendations are often issued by strategists allegedly rotating among industries in reaction to macroeconomic shocks, we include in the model a dummy for the

[18] The table actually includes seven brokers. Lehman Brothers. was replaced during 2008 by Barclays. Also, IBES does not have any industry recommendation from Bear Stearns and CSFB in 2009.

[19] During the year 2002 coverage is lower because our sample period only starts in September of that year. In 2008 we see a decline in industry coverage of CIBC and CSFB.

NBER recessions. During our sample period there were two expansions and one recession (from December 2007 to June 2009). We also include another dummy classifying an industry as either cyclical or non-cyclical depending on its sensitivity to the business cycle. Our classification follows Barra (2009), and identifies as cyclical the industries belonging to the Materials, Industrials, and Information Technology sectors (GICS sectors 15, 20, and 45). We then consider the interaction between these two variables to test for sector rotation in the issuance of industry recommendations.

Underwriting activity is largely firm-specific. Thus, unlike in firm recommendations, one may not expect conflicts of interests associated with underwriting to affect industry recommendations. Nevertheless, to control for the possibility that analysts are more optimistic about industries that have a high IPO/SEO activity we include three variables related to equity underwriting activity. The first two are the total and average IPO/SEO proceeds in the industry during the year preceding the recommendation. These variables capture the volume of equity issuance in the industry. The last variable is the percentage of IPO/SEO proceeds in an industry underwritten by the issuing broker during the two years preceding the recommendation, out of all IPO/SEO proceeds underwritten by this broker during that time period. This variable is close in spirit to the "affiliation" variable used in prior research to proxy for conflicts of interest at the firm level [Lin and McNichols (1998); Michaely and Womack (1999)]. We control for broker fixed effects to account for any broker-specific time invariant characteristics. We cluster the standard errors at the broker-industry level.

Table 2 presents the results of logit models based on the explanatory variables above. For this analysis we drop reiterations, i.e. observations with the same industry recommendations from a particular broker in each month. Thus, we only keep one observation per industry-month from any given broker except in cases in which the industry recommendation changed during the month. We use two specifications. In the first (second) specification the dependent variable is a dummy equal to one when the industry recommendation is optimistic (pessimistic) and zero otherwise.[20] Consider the first specification. The probability of issuing an optimistic industry recommendation is increasing in the average profitability, R&D, and Capex intensity in the

[20] Note that the two specifications are not mutually independent. They reflect the same set of results viewed from two different angles. It would have been desirable to pool the two separate logistic models into a single ordered-logit model. However, this is not possible, since the Wald test rejects the parallel regression assumption, implying that an ordered-logit (and similarly an ordered-probit) is not valid in this case. See Long and Freese (2006: p. 197-200) for details.

industry, and decreasing in the market-to-book ratio. For example, for the median industry, a one standard deviation increase in R&D intensity increases the probability of issuing an optimistic industry recommendation by 4.1 percentage points.[21] We also observe a momentum effect as the probability of issuing an optimistic industry recommendation is increasing in the industry returns during the two quarters preceding the recommendation.

Analysts tend to favor cyclical industries during booms as reflected in the positive coefficient on the cyclical dummy. However, cyclical industries fall out of favor during recessions as reflected in the interaction term between the cyclical and recession dummies, in line with a sector rotation approach. Finally, we observe some mixed evidence on the tendency of brokers to issue an optimistic recommendation to industries in which there is more underwriting activity as the coefficient on the total volume of IPOs/SEOs in the industry is positive, while the coefficient on the average offering size is negative.

*<Insert Table 2 here>*

Similar to the optimistic model, the pessimistic model shows that high R&D and Capex activities are less likely to be associated with a pessimistic industry recommendation. Like the optimistic model, we observe a strong momentum effect. There are also hints of the sector rotation strategy playing a role here: analysts are less likely to issue a pessimistic recommendation to cyclical industries during booms (that is, when the cyclical dummy is 1 and the recession dummy is 0) and to non-cyclical industries during recessions (when the cyclical dummy is 0 and the recession dummy is 1). Finally, underwriting activity does not seem to affect the probability of issuing a pessimistic industry recommendation.

We also conducted but did not tabulate alternative specifications for Table 2. First, we use the average industry recommendation per broker or across brokers within a given month as dependent variables. Each dependent variable is left censored at 1 and right censored at 3. To account for that, we estimate a Tobit model. Second, we use an upgrade/downgrade approach to define our dependent variables based on changes in industry recommendations. The conclusions from these alternative models are similar.

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[21] For the median firm, the marginal effect of R&D (from Table 2) is 0.96, and the standard deviation of R&D is 0.0433 (not tabulated).

## 4 Analysts' Across-Industry Expertise

There is an extensive literature showing that firm-level analysts add value with their firm recommendations [see for example Stickel (1995); Womack (1996); Barber, Lehavy, McNichols, and Trueman (2001, 2006); Jegadeesh, Kim, Krische and Lee (2004); and Barber, Lehavy, and Trueman (2010)]. There is also evidence that analysts possess within-industry expertise reflected in their ability to rank firms within industries [Boni and Womack (2006)].[22] A natural question that arises is whether analysts (firm-level or strategists) have across-industry expertise that allows them to make informative predictions regarding the prospects of industries.

Industry analysis in sell-side research is implemented by a combination of the work of analysts in the strategy group and the traditional firm-level analysts. The way firm-level analysts are organized can foster within-industry rather than across-industry expertise. The coverage universe of each such analyst is typically concentrated in one industry, naturally facilitating the task of ranking firms relative to their industry peers. But organizing firm-analysts by industry can rather imperil their ability to assess the prospects of their industry relative to others. Recall, though, that the main source of across-industry analysis in sell-side research resides with the strategists. For them the task of differentiating among industries is part of the job profile. The two types of analysts thus complement each other. Jointly, they have access to a synthesis of top-down macroeconomic data and bottom-up aggregated firm-specific knowledge, putting them in a good position to identify "hot" and "cold" industries.

On the other hand, some prominent features of industry recommendations make their investment value less obvious. Generating such recommendations requires skill and experience, but they are largely based on widely available macroeconomic data, diminishing any informational advantage. Moreover, unlike with firm recommendations, our data does not allow us to identify the exact date at which the industry recommendation is issued. Rather, we can only identify whether a brokerage-house changed its industry recommendation within a month. This diminishes our ability to identify across-industry expertise, even if it exists.

The analysis in this section explores whether analysts have across-industry expertise by analyzing the returns of portfolios constructed based on industry recommendations. That is, we

[22] The literature has also explored within-industry expertise as revealed by analysts' ability to generate better earnings forecasts for the firms they follow. The idea is that greater industry focus allows the analyst to have better forecasts at the firm level [e.g., Jacob, Lys and Neale (1999), Clement (1999), and Dunn and Nathan (2005)].

ask whether an investor would have obtained abnormal returns, had she followed up on the recommendations by investing in these portfolios. This is the common approach used to test for information in firm recommendations [e.g., Barber, Lehavy, McNichols, and Trueman (2001, 2006), Boni and Womack (2006), and Barber, Lehavy, and Trueman (2010)].[23]

### *4.1 Recommendation Portfolios*

We first aggregate the industry recommendations to create monthly consensus industry recommendations. To avoid neglected industries, facilitate aggregation of information across brokers, and to mitigate some of the errors associated with GICS misclassification (see Section 2.3) we compute the average industry recommendation of industries for which we have at least three recommendations during a month. In Appendix III we provide a formal discussion of how this approach diminishes the mismeasurement associated with the industry classification error. We compute the monthly consensus by averaging all the industry recommendations issued during that month by all the brokers in our sample.[24] To illustrate, assume that brokers issued 10 recommendations for firms in the Media industry in month *t*, then the consensus recommendation for the Media industry would be the average of the industry recommendations recorded from the 'btext' field in those 10 recommendations. This approach allows us to capture changes in industry recommendations during a month. For example, if a broker changed her recommendation for the Media industry from '1' to '2' during the month, then the consensus for month *t* will be affected by this change.

By aggregating industry recommendations from different brokers we reduce the idiosyncratic component associated with the signal obtained by each broker. Note that finding across-industry expertise associated with a consensus measure is indicative of such expertise at the individual analyst level. Indeed, if individual analysts' signals were pure noise, then their aggregations would have no value to investors.[25]

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[23] Another common approach involves looking at investors' short-term reactions to newly issued recommendations. Since this approach depends on knowing the exact recommendation issuance day, it cannot be applied here.

[24] Notice that the term consensus here is short for the average of recently issued (that is, issued in the current month) recommendations. This contrasts with the meaning of consensus adopted by many papers in the literature, in which it refers to the average of *all* recommendations that are outstanding in a specific moment. Thus, our approach for measuring the consensus avoids stale recommendations at the cost of being less comprehensive.

[25] Our approach to aggregating recommendations is similar in spirit to what has been done in the firm-level analysts' literature. For example, Barber et al. (2006) construct portfolios to which they add firm recommendations, and whose returns are effectively returns to aggregate recommendation portfolios and Boni and Womack (2006) build an aggregate variable based on recommendations of different analysts.

Next, in each month $t$ we refer to the consensus recommendation for an industry as "optimistic" if this consensus is less than or equal to 1.5. We refer to the consensus recommendation as "pessimistic" if it is greater than or equal to 2.5. In all other cases, we refer to the consensus as "neutral." We then construct three industry portfolios based on *changes* in the consensus for each month $t$. Portfolio UI (for 'Upgrade Industry') in month $t$ consists of all industries that were upgraded to "optimistic" during month $t$-1, Portfolio DI (for 'Downgrade Industry') consists of all industries that were downgraded to "pessimistic" during month $t$-1, and Portfolio NI (for 'Neutral Industry') consists of all industries that were either upgraded or downgraded into the "neutral" consensus during month $t$-1.[26] This approach of building investment portfolios based on changes (revisions) in recommendations is consistent with literature on firm recommendations [e.g. Jegadeesh, Kim, Krische and Lee (2004); Barber, Lehavy, McNichols and Trueman (2006); Barber, Lehavy and Trueman (2010)].

*<Insert Table 3 here>*

Panel A of Table 3 presents summary statistics related to the three portfolios and the portfolio formation procedure. First, note that Portfolios UI and NI are well defined in all 87 months of our sample period. By contrast, Portfolio DI (the downgrade to pessimistic portfolio) is only defined in 65 months. Thus, there are 22 months in which there aren't any industries whose consensus was downgraded to "pessimistic." The average number of industries belonging to Portfolios UI, NI, and DI in a given month is 5.5, 10.4, and 2.8, respectively.

Panel A of Table 3 reveals that the different industries are quite evenly distributed among the three portfolios. Over our sample period 65 out of the 68 industries belonged to Portfolio UI at some point. Portfolio DI is the least represented, but still around two thirds of the industries belonged to this portfolio at some point. This suggests that the classification to the three portfolios is not degenerate, and can potentially contain information.

### *4.2 Raw Returns*

Using CRSP data we calculate a monthly return for each one of the three portfolios in two steps. First, we calculate a month $t$ industry return for each one of the GICS industries. This is the value-weighted return across all CRSP firms in the relevant industry, where the weights are

[26] In unreported results, we also examine breaking down Portfolio NI, depending on whether an industry was upgraded or downgraded towards "neutral." None of the conclusions presented in the paper changes under this different breakdown.

based on market values at the end of month *t*-1.[27,28] Second, we calculate the monthly return for portfolios UI, NI, and DI as the equal weighted return of all industries in the relevant portfolio.

Panel B of Table 3 reports raw monthly returns related to different time periods for each of the three portfolios. To interpret the results, recall that portfolios in month *t* are formed based on consensus industry recommendations in month *t*-1. Consider first the average returns in month *t*-1. They are monotonically decreasing as we move from Portfolio UI (1.3%) to Portfolio DI (-0.2%, insignificant). A similar trend is observed in month *t*-2. Consistent with the logit results, these trends suggest that analysts chase industry momentum. Consider now the returns in month *t*. These reflect the returns to portfolios constructed based on the industry recommendations issued in the previous month. The monthly return on Portfolio UI is 1.3% which is significantly different from Portfolio DI's return of 0.1%. Moreover, a hedged portfolio long in Portfolio UI and short in Portfolio DI, during the 65 months in which Portfolio DI exists, yields a significant 1.4% per month. When examining the returns of the different portfolios starting from month *t*+1, we do not find a significant difference between the three portfolios, except in the case of 12 months returns. Note, however, that these are buy-and-hold returns that do not take into account changes in recommendations during the holding period. In the next section we examine long-term abnormal returns using a more reasonable approach that takes into account subsequent changes in consensus industry recommendations.

### *4.3 Risk-Adjusted Returns*

We next turn to evaluating whether portfolios based on industry recommendations can generate *abnormal* returns. We estimate both in-sample and out-of-sample alphas of the three industry portfolios relative to the Fama-French four factors (excess market return, HML, SMB, and UMD). For our in-sample analysis we regress the excess returns of the different portfolios on the four Fama-French factors over a period of 60 months similar to Barber, Lehavy, McNichols, and Truman (2001, 2006). The intercept from this regression is an estimate of the in-sample alpha. Our out-of-sample approach is similar to Brennan, Chordia, and Subrahmanyam (1998)

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[27] The most obvious and least costly way to "buy" or "sell" an industry is to buy or sell the appropriate industry ETF. By calculating the industry return as a weighted average of all CRSP firms in this industry we essentially replicate the return on the corresponding industry ETF.
[28] If a firm is delisted at time *t*, its monthly return plus its delisting return from CRSP are used in the computation of its industry return. If a firm has a missing return at time *t*, we exclude it from the computation of the industry return. In a robustness test we replace missing returns of a firm in month *t* with the market return during that month; results are not sensitive to this change.

and Chordia, Subrahmanyam, and Anshuman (2001). For each month in our sample period, we regress the monthly excess returns of the three industry portfolios on the returns of the Fama-French four factors during the preceding 60 months. Thus, for each month we obtain an estimate of the factor loadings. Next, for each month we calculate the out-of-sample alpha as the realized excess return of the portfolio less the expected excess return calculated from the realized returns on the factors and the estimated factor loadings. For each of the three portfolios we thus obtain a time series of out-of-sample alpha estimates. We can then use a t-test to estimate whether the average alpha is significant.

In both analyses we include the abnormal returns obtained from a short-term investment of one month, and longer term investments of 3, 6, and 12 months. In the long-term analyses we assume that investors keep track of recommendations and change their portfolio accordingly. Thus, we keep an industry in the portfolio as long as its average industry recommendation does not negate the original signal or until the end of the horizon. For example, if an industry is upgraded to optimistic in a given month and enters into portfolio UI, we keep it in the portfolio as long as its monthly average recommendation remains within the optimistic threshold (or no new industry recommendation is available) or until the end of the investment horizon.

Consider first the returns using the one-month horizon presented in Table 4. Both the in-sample (Panel A) and the out-of-sample (Panel B) analyses show a positive and significant alpha for the optimistic portfolio and a negative and significant alpha for the pessimistic portfolio. For example, the average out-of-sample alpha of portfolio UI is 0.59% per month, significant at the 1% level. By contrast, portfolio DI generates a negative out-of-sample alpha of 0.9% per month. A hedged portfolio long in portfolio UI and short in portfolio DI yields a significant abnormal return of about 1.4% per month both in- and out-of-sample sample.[29]

*<Insert Table 4 here>*

Now, consider the abnormal returns associated with longer investment horizons. Here the results are somewhat different in the two analyses. In the in-sample analysis presented in Panel A we still find abnormal returns for investment horizons of up to 12 months. For example, the long-short portfolio in Panel A shows significant abnormal returns for 3, 6, and 12 month horizons.

[29] Note that the hedged portfolio can only be held about 9 months in each year because portfolio DI only exists about 75% of the time. Hence an estimate of the annualized abnormal return of the hedged portfolio is 1.4%*9=12.6% (assuming that whenever portfolio DI does not exist, the investment strategy has zero alpha).

By contrast, in the out-of-sample analysis the results do not suggest any long-term predictability. We interpret these results as saying that, to the extent that there is a long-term value in the recommendation portfolios, it is weaker than in the short term.

For robustness we performed the same analysis relaxing the requirement of at least three recommendations for an industry to calculate the monthly average. The results are similar to those in Table 4, although they are somewhat smaller in magnitude. This is consistent with our expectation that removing the requirement is likely to increase the frequency of industry misclassifications, and thereby weaken the informativeness of the industry consensus.

One might also wonder whether the results are attributed exclusively to a "bull" or a "bear" market. Note that our time period covers both, and in particular it includes the recent global financial crisis as well as the "bull" markets that preceded and followed it. As a robustness check, we test whether the results of Table 4 are reversed during the bear market of 2008. Of course, any such analysis is suggestive only, as it is based on just 12 monthly observations. We find that the in-sample and out-of-sample alphas for these 12 months are insignificant over almost all investment horizons, which is what one would expect given the lack of power. Moreover, we cannot reject the hypothesis that the alphas for 2008 are equal to the alphas during the rest of our sample period. Thus, it appears that the results are not reversed during the bear market of 2008.

The predictive value of industry recommendations may seem surprising, particularly given that our portfolios are formed based on industry recommendations that are potentially stale. Indeed, the portfolios are formed only at the end of each month. It is important to note, however, that much of the predictability that we identify comes from short selling a small group of industries that are in Portfolio DI (see Panel A of Table 3). The difference between the abnormal returns in Portfolios UI and NI (which together account for more than 90% of the industries) is not statistically significant.

As a final robustness test we also examine the relation between industry recommendations and future industry performance proxied by return on assets (ROA), controlling for current and past ROA. The results (available upon request) suggest that more optimistic industry recommendations are associated with higher industry ROA for up to four quarters following the recommendations. These results are consistent with analysts possessing expertise in identifying industries with future favorable fundamentals, lending credence to our main analysis of returns.

### *4.4 Discussion*

Collectively, the evidence so far suggests that analysts possess across-industry expertise, and can identify "hot" and "cold" industries over short horizons of one month. When it comes to longer horizons the evidence is less conclusive and is limited to the in-sample analysis.

It is worth emphasizing the considerable controversy regarding the investment value of analysts' outputs. Generally, the literature on analysts' forecasts did not find conclusive evidence of subsequent superior stock price performance. With recommendations the evidence is mixed. Several studies (e.g., those discussed in the Introduction) argue that analysts' stock recommendations are informative. However, Altinkilic and Hansen (2009) are skeptical of this evidence, arguing that same-day price reactions associated with stock recommendations merely reflect firms' specific news released shortly before the recommendations were issued.

Note that our conclusion regarding the across-industry expertise of analysts is not likely to be subject to this criticism. First, our exploration of across-industry expertise relies on industry-level recommendations. These recommendations are typically issued by strategists for all industries at the same time, as opposed to firm recommendations which are issued sporadically for each firm in response to firm specific news. Thus, it is hard to argue that the returns we identify just reflect strategists "piggybacking" on some industry-specific news. Second, even if industry recommendations just follow some news events, our empirical approach eliminates the spurious predictability discussed in Altinkilic and Hansen (2009) by relying on stale recommendations only. Indeed, we construct our portfolio only at the end of the month in which the recommendations become available on IBES. Thus, any news-related same-day returns that might have triggered the issuance of the recommendations are excluded from the analysis.

The evidence in Ljungqvist, Malloy, and Marston (2009) also casts doubt on predictability results associated with analysts' recommendations. They show that some of the return predictability found by researchers stems from problems with the IBES data from 2002-

2004. The IBES files we used were downloaded in 2008 and 2009, and to the best of our knowledge are free from these data problems.[30]

## 5 Relation between Across-Industry and Within-Industry Expertise

In the previous section we presented evidence consistent with analysts' across-industry expertise as reflected in the investment value of their industry recommendations. In this section we explore the relation between across-industry and within-industry expertise. Specifically, we examine to what extent industry and firm recommendations are related, whether they reflect distinct pieces of information, and whether they can be jointly used to enhance the investment value of analysts' recommendations.

### *5.1 Preliminary Analysis*

It seems reasonable that industry and firm recommendations are at least somewhat related. Consider first a top-down approach (mostly taken by strategists). Under this approach the analyst collects and analyzes macroeconomic data, demand and supply information, etc. This analysis helps the analyst understand the prospects of each industry (across-industry expertise), but also is useful in evaluating the prospects of each firm in the industry (within-industry expertise). From a bottom-up perspective (mostly used by firm-level analysts), an analyst can study many firms in the industry (within-industry expertise) and then extract common aspects that help her understand the prospects of the industry as a whole compared to other industries (across-industry expertise). Both approaches suggest that the outlooks expressed at the industry and firm levels should be related. On the other hand, relatedness does not imply perfect alignment between recommendations at the industry and firm levels. In fact, one can view a firm's prospects as driven by two components, one linked to its industry's overall prospects and the other associated with the firm's idiosyncratic characteristics – allowing, for example, for existence of winners and losers in the same industry. Moreover, industry and firm recommendations may be misaligned since they are often determined by analysts in different groups, which may not be perfectly coordinated. Therefore, we expect the outlooks expressed at the industry and firm levels to be related, but only to a certain degree.

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[30] We thank Alexander Ljungqvist and Felicia Marston for advising us on this issue.

*<Insert Table 5 here>*

Table 5 provides a preliminary look at the interaction between industry and firm recommendations. As with industry recommendations, we map firm recommendations into three levels, coding optimistic recommendations ("strong buy" or "buy") as '1', neutral recommendations ("hold") as '2', and pessimistic recommendations ("sell" or "strong sell") as '3'.[31] The table reveals a significant variation in firm recommendations within each level of industry recommendation. For example, out of the firm recommendations issued with an optimistic industry recommendation, 42% are rated optimistic, 45% are rated neutral, and 13% are rated pessimistic. We also see a wide dispersion of firm recommendations issued with neutral and pessimistic industry recommendation. The average firm recommendation for firms in industries rated as optimistic is 1.71, in industries rated neutral is 1.81, and in industries rated pessimistic is 1.96 – and the differences between these numbers are significant. Thus, there is some positive correlation between industry and firm recommendations. However, the dispersion in firm recommendations for a given level of industry recommendation suggests that industry and firm recommendations contain different information.

### *5.2 The Benchmark for Firm Recommendations*

To better understand the relation between within- and across-industry expertise, it is necessary to know whether firm recommendations reflect information about the industry. That is, does a 'buy' recommendation issued to a firm reflect a buying opportunity relative to the entire market, or relative to industry peers?

If firm recommendations are benchmarked to industry peers, then firm and industry recommendations should contain orthogonal information. While industry recommendations forecast the outlook for the industry as a whole, firm recommendations forecast the deviations of specific firms from the industry outlook. In this case, industry recommendations have independent value to investors. Furthermore, firm specific recommendations should not be interpreted outside of their industry context. Hence, combining industry and firm recommendations would add value to investors.

If, on the other hand, firm recommendations are benchmarked to the market, then they incorporate both systematic industry information (across-industry) as well as firm-specific

[31] Given that our sample period starts in September 2002, most of the brokers follow a 3-tier rating scheme for their firms recommendations. See Kadan, Madureira, Wang, and Zach (2009).

information (within-industry). If, in addition, firm-level outlooks are used as inputs when industry outlooks are established (e.g., through proper sharing of information between strategists and firm-level analysts), we expect industry recommendations to reflect an aggregation of firm recommendations. In this case, industry recommendations are to some extent a repackaging of multiple firm recommendations, and they do not carry much incremental value to investors beyond firm recommendations. Under this scenario, combining industry and firm recommendations would not add much value to investors (less than the value in the case of recommendations benchmarked against the industry).

### 5.2.1 Analysis of Brokers' Disclosures

In order to understand how firm recommendations are benchmarked, we start by examining the disclosures of analysts regarding the meaning they assign to their firm recommendations. Under regulations NASD Rule 2711 and NYSE Rule 472, which were adopted prior to the beginning of our sample period, analysts are required to disclose the meaning of their recommendations inside their reports. We examined these disclosures for the 20 largest brokers (in terms of numbers of recommendations). Table 6 summarizes our findings. Out of the 20 brokers, 10 brokers state that they benchmark their firm recommendations to industry peers – including the six largest brokers in our industry recommendations sample. We refer to these brokers as "industry benchmarkers." For example, in the case of CIBC, analysts rate individual stocks based on the "stock's expected performance vs. the sector." In contrast, the other 10 brokers state that they benchmark their recommendations to the entire market or to a specific threshold return. We refer to such brokers as "market benchmarkers." For example, Wachovia's analysts rate a stock based on the stock's expected performance "relative to the market over the next 12 months." Thus, the disclosures in Table 6 suggest that brokers differ, according to their statements, in their interpretation of firm recommendations.

*<Insert Table 6 here>*

### 5.2.2 Pseudo Industry Recommendations

The fact that brokers state that they use a specific benchmark is anecdotal only. We next examine empirically which benchmark is in fact being used. As explained above, if brokers use an industry benchmark for their firm recommendations, then their firm recommendations will contain no industry-wide information. By contrast, if brokers use a market benchmark, then their firm recommendations will have information regarding industry outlook. This observation enables us to construct a simple test as follows. In each month we construct a "pseudo industry recommendation" by value weighting all recommendations issued during that month to firms belonging to the specific GICS industry. That is, the pseudo industry recommendations mirror the "true" industry recommendations studied in the paper. Only that, instead of obtaining them directly from IBES, we construct them by aggregating firm recommendations on an industry level [similar to Boni and Womack (2006)].

*<Insert Table 7 here>*

Panel A of Table 7 presents summary statistics of pseudo industry recommendations. First, the average pseudo industry recommendation for all brokers is 1.62. By comparison, the average real industry recommendation is somewhat less optimistic at 1.85. We then distinguish between two sets of brokers based on the analysis in Table 6. The average pseudo industry recommendation for industry benchmarkers is 1.71, while the average for market benchmarkers is a bit more optimistic at 1.62. Overall, there does not seem to be a large economic difference between the two sub-groups in the level of their recommendations.

Panel B of Table 7 presents the correlation matrix between the different types of pseudo industry recommendations and the true industry recommendations. There is little correlation between the pseudo industry recommendations and the true industry recommendations. These correlations range from 0.10 to 0.15, suggesting that true industry recommendations are very different in their informational content from just an aggregation of firm recommendations. For the industry benchmarkers the correlation is 0.14. Such a low correlation is expected given these brokers' claims that their firm recommendations are benchmarked to industry peers – and thus are not expected to contain much industry information. The more surprising result is that the correlation between the true and pseudo industry recommendations among the market benchmarkers is still just 0.10. Here we would expect pseudo industry recommendations to somewhat reflect across-industry expertise, and thus be more correlated with industry outlooks. The low correlations we find raise the possibility that while market benchmarkers state that they use a market benchmark for their firm recommendations, in practice they may still benchmark to industry peers.[32]

[32] Note that the "true" industry recommendations in this case are typically *not* issued by the market benchmarkers. Therefore, another alternative, of course, is that market benchmarkers have strikingly different views about industry prospects when compared to the views expressed in the explicit industry recommendations by the brokers in our sample.

To more formally investigate this issue we repeat the analysis from Table 4 using the pseudo industry recommendations. Boni and Womack (2006) conduct a similar analysis.[33] The idea is that if pseudo industry recommendations reflect across-industry expertise and have predictive information regarding the industry, then portfolios based on pseudo industry recommendations will demonstrate abnormal returns. Panel C of Table 7 presents the results. As in Tables 3 and 4, we define portfolios of upgraded, neutral, and downgraded industries based on changes in industry outlooks, except that this time the industry outlooks are expressed by pseudo industry recommendations. More specifically, in each month we sort industries by their consensus pseudo industry recommendation and define the portfolios PUI (for pseudo upgraded industries), PNI (pseudo neutral industries), and PDI (for pseudo downgraded industries). Then, we calculate the one month in-sample and out-of-sample alphas of the three portfolios and of a portfolio that is long in Portfolio PUI and short in Portfolio PDI.

Consider first the results for all brokers (both in-sample and out-of-sample). The alphas are not different from zero for the three portfolios as well as for the long-short portfolio. This is consistent with the findings of Boni and Womack (2006, page 106). Similar results obtain for the industry benchmarkers. The results for market benchmarkers are different. The in-sample results show significantly positive alphas for portfolio PUI and significantly negative alphas for portfolio PDI. The long-short portfolio is also statistically significant. The out-of-sample alphas are somewhat weaker as only the upgraded portfolio shows significance. These results are consistent with the disclosure of these brokers, and suggest that firm recommendations issued by market-benchmarkers reflect some industry expertise.

Our conclusion from this analysis is that it is important to pay attention to the benchmark used by brokers for their firm recommendations when examining the across-industry information incorporated in them. For industry benchmarkers the results show that true industry recommendations are different from just an aggregation of firm recommendations. While the former contains information regarding industry outlooks and reflects analysts' across-industry expertise, the latter does not reflect that expertise. This is in line with the low correlation between the real- and pseudo-industry recommendations, documented in Panel B. Among market

[33] The focus of our paper is on true industry recommendations, which is different from Boni and Womack (2006) who did not have access to such recommendations. Howe, Unlu, and Yan (2009) conduct an analysis somewhat similar to that of Boni and Womack (2006), but they focus on excess returns relative to the market rather than risk-adjusted abnormal returns.

benchmarkers, where we do expect pseudo industry recommendations to somewhat reflect across-industry expertise, we find some predictive power (mostly in the in-sample analysis). Thus, our results provide more nuanced conclusions regarding the across-industry information in aggregations of firm-recommendations than those in Boni and Womack (2006). It is worth emphasizing that Boni and Womack (2006) employ data before 2002, a period during which brokers were not required to disclose their benchmarks.

Two caveats are in order regarding comparisons between pseudo and true industry recommendations. First, it is often the case that we do not obtain firm recommendations for all firms in the industry in any given month. For this simple reason, true industry recommendations are likely to contain more information than pseudo industry recommendations. Second, the potential misalignment between analysts' definitions of industries and the GICS definition might create a further rift between true and pseudo industry recommendations.

### *5.3 Combining Across- and Within-Industry Expertise*

The results so far suggest that true industry recommendations reflect across-industry expertise and carry value to investors that is unrelated to information in firm recommendations, and more so for industry-benchmarkers. Prior research demonstrates that firm recommendations also have investment value. Jointly, these two observations suggest that combining firm and industry recommendations will enhance their value to investors. Such combinations would reflect both within- and across-industry expertise of analysts. In this section we explore this idea.

A reasonable approach to exploit both aspects of expertise consists of first selecting industries using industry recommendations, and then using firm recommendations to choose firms within the selected industries. This approach extracts the full power of analysts' knowledge as it incorporates their signals both within-industry (mostly driven by a bottom-up analysis) and across industries (mostly driven by a top-down analysis).

As a start, we follow Boni and Womack (2006) in classifying firms based on upgrades and downgrades in *firm* recommendations. For each firm covered by IBES and each month during our sample period, we count the number of upgrades and downgrades that the firm received. An upgrade or downgrade is defined at a firm-broker level. For example, an upgrade on firm *i* by broker *B* in month *t* means that *B* issued a recommendation for *i* in month *t* that was more optimistic than the most recent recommendation issued by B to *i*. Thus, we ignore reiterations of recommendations, or initiations of coverage. We then compute the difference between the number of upgrades and the number of downgrades for each month and firm across all brokers. If the difference is positive, then the firm is a "net upgrade." Conversely, if the difference is negative, then the firm is a "net downgrade."

*<Insert Table 8 here>*

We next combine firm and industry recommendations. In each month we perform a double-sort of the universe of firms based on the firm classification (whether "net upgraded" or "net downgraded") and on its industry classification (belonging to either one of the three industry portfolios described in the previous section) that were prevailing in the previous month. Therefore, within each of the three industry portfolios, we form two portfolios based on firm recommendations, one for the net upgraded firms (Portfolio UF) and one for the net downgraded firms (Portfolio DF).[34] This generates six portfolios of firms. For example, (UI,UF) is the portfolio of net upgraded firms in upgraded industries. Returns on each portfolio are obtained from equal-weighting the returns on their stocks. Similar to the analysis in Section 4.3, we analyze in-sample and out-of-sample abnormal returns obtained from a short investment horizon of one month, and longer horizons of 3, 6, and 12 months. The abnormal returns of the double-sorted portfolios are reported in Table 8.

Consider first the one-month horizon. Both the in-sample and out-of-sample results support the idea that combining industry and firm recommendations enhances investment value. For example, whether net upgraded firms show abnormal returns depends on their industry outlook: such net upgraded stocks have significantly positive alphas if they are part of the industries with optimistic outlook (UI,UF) or neutral outlook (NI,UF), but not when they are part of the industries with the worst outlook (DI,UF). In a similar fashion, net downgraded stocks have significantly negative alphas when part of a pessimistic industry (DI,DF), but not when they are part of an optimistic industry (UI,DF) or a neutral industry (NI,DF). In fact, when a firm is a net downgrade but belongs to an industry in Portfolio UI, it generates *positive* abnormal returns in both the in-sample and out-of-sample analyses. A trading strategy long in the top-left portfolio (UI,UF) and short in the bottom-right portfolio (DI,DF) yields a monthly abnormal return of over

[34] Notice that a third "portfolio" is implied here, the one with firms that were neither "net upgraded" nor "net downgraded." In fact, about half of the firms receiving recommendations in the month would be in this third "portfolio", either because they only receive reiteration/initiations of recommendations, or because the number of upgrades is equal to the number of downgrades.

3% in both analyses. These returns are larger than those obtained in Table 4 using industry recommendations only.

For the longer investment horizons we follow a methodology similar to that used in Section 4.3. That is, we include a firm in a portfolio until the end of the investment horizon or until the signal (on either the firm or the industry) changes. If there are no new recommendations (for either the firm or the industry) in a given month, we assume that the signal remains consistent in that month.[35] The alphas for longer investment horizons up to 12 months are consistent in sign and significance but somewhat lower in magnitude compared to the one-month results. For example, when examining in-sample alphas over a 12-month horizon, a portfolio long in (UI,UF) and short in (DI,DF) yields a monthly abnormal return of 2.3%.

Given that firm recommendations carry different meanings for market- and industry-benchmarkers, it is interesting to repeat this analysis separately for these two groups. Since industry-benchmarkers aim only at ranking firms within industries, the combination of industry- and firm-recommendations is likely to be especially beneficial for investors when considering the recommendations of such analysts. By contrast, for market-benchmarkers, firm recommendations already reflect some industry outlooks, and combining the two types of recommendations is likely to add less value to investors for such analysts. Our data only allows us to directly test the first of these two assertions, because the vast majority (97.8%) of industry recommendations in our sample are issued by brokers that rely on an industry benchmark. As expected, when we restrict attention to industry benchmarkers only, the results corresponding to Table 8 (untabulated for brevity) become stronger. For example, for the one month investment horizon, a portfolio long in (UI,UF) and short in (DI,DF) generates an out-of-sample alpha of 3.7% and an in-sample alpha of 5%.

Overall, the results in this section reinforce the conclusion that industry recommendations contain information that is not already incorporated in firm recommendations. While firm recommendations often reflect within-industry expertise and focus on ranking stocks within industries, industry recommendations reflect across-industry expertise enabling investors to rank

[35] Notice that Boni and Womack (2006) focused on one month returns only. Therefore, for horizons beyond one month, our methodology extends theirs by allowing the firm’s and industry’s signals to remain valid for up to 12 months. An alternative is to allow the classification of industries to be extended to long horizons while still using one month-ahead returns with respect to the firm’s signal. Results (unreported) of this alternative yield similar conclusions.

industries. Thus, combining the two types of recommendations exploits both dimensions of analysts' industry expertise and generates investment portfolios that outperform portfolios based on just one type of recommendation (firm or industry).

## 6 Alternative Explanations

While the results in the previous sections are consistent with analysts possessing across-industry expertise, they may also be consistent with two alternative explanations, which we consider in this section.

### *6.1 Industry Momentum*

It may be that analysts do not possess any expertise in analyzing the prospects of different industries. Rather, they just chase industry momentum providing no added value beyond it. In this case, the abnormal returns we observe are nothing but a result of this well documented phenomenon [Moskowitz and Grinblatt (1999)]. In this section, we conduct several tests to explore this possibility.

First, in each month during our sample period we assign each GICS industry into one of three momentum portfolios based on prior six months returns as follows. Momentum Portfolio MOM1 contains industries in the top 15% of the prior-return distribution; Momentum Portfolio MOM3 contains industries in the bottom 15% of the prior-return distribution, and Momentum portfolio MOM2 contains all the rest of the industries. We choose these cutoffs to be as consistent as possible with Moskowitz and Grinblatt (1999), who define winner (loser) industries as the top (bottom) three out of a total of 20 industries. We then double sort the industry-month observations based on their assigned industry recommendations and industry momentum portfolios. The results are reported in Panel A of Table 9, and indicate only a mild positive correlation between industry recommendations and industry momentum. For example, when considering industries assigned to recommendation portfolio UI (optimistic), 18% of them exhibit high momentum (momentum portfolio MOM1), 70% are in momentum portfolio MOM2, and 12% exhibit low momentum (momentum portfolio MOM3). Out of the industry-month observations that belong to recommendation portfolio UI (pessimistic), 10% show high momentum, 69% show moderate momentum, and 21% show negative momentum. These results show that, while a positive correlation exists, analysts do not blindly follow industry momentum.

*<Insert Table 9 here>*

Next, note that if analysts were defining their industry recommendations based mostly on past performance, our strategy for forming portfolios based on recommendations would be at best an imperfect replica of the industry momentum strategy. In this sense, an industry momentum strategy like in Moskowitz and Grinblatt (1999) should yield "better" or cleaner results than our strategy. Thus, we compare the one-month abnormal returns of the long-short strategy resulting from the industry recommendation portfolios to those obtained from a long-short momentum strategy. The results of this test are reported in Panel B of Table 9. For both the in-sample and out-of-sample analysis, neither momentum portfolio MOM1 nor portfolio MOM3 exhibit significant abnormal returns in the month following their formation. The return on the hedged portfolio is insignificant in the in-sample analysis, and surprisingly negative in the out-of-sample analysis. More importantly, the difference between the alpha of the long-short recommendation portfolio and that of the momentum portfolio is positive and highly significant (p-value lower than 0.01), indicating that the abnormal returns associated with the recommendation portfolio are not attributed to industry momentum.

In our next test we attempt to directly isolate the effects of industry momentum on industry recommendations. We do so by excluding from recommendation portfolio UI all industries that belong to momentum portfolio MOM1. That is, we only consider industries that have high industry recommendations but do not exhibit high past returns. Similarly, we exclude from industry recommendation portfolio DI all industries belonging to momentum portfolio MOM3. The one-month abnormal returns are reported in Panel C of Table 9. For both the in-sample and out-of-sample analysis the long-short portfolio exhibits a positive and highly significant alpha. This is a strong indication that industry momentum is not responsible for the observed abnormal returns on industry recommendation portfolios.

As a final test for the "momentum hypothesis" we checked the return predictability of industry recommendations using the Fama-MacBeth cross-sectional approach. This allows us to control for different characteristics affecting stock returns (such as momentum) directly, rather than using a factor approach. For each month in our sample we estimated a cross-sectional regression with industry excess returns as a dependent variable, and industry characteristics as independent variables. The characteristics we used are: beta, size, book-to-market, momentum, and the industry-consensus portfolio to which the industry belongs (*Port*) or the industry consensus recommendation (*Ind_Rec*). For this analysis we set Port to equal 1, 2, or 3 when the industry belongs to industry portfolio UI, NI, or DI, respectively. We then average the coefficients over time and use a t-test to examine their statistical significance. The results are reported in Panel D of Table 9. We observe a significantly negative coefficient on either *Port* or *Ind_Rec*, indicating that industry recommendations have predictive ability with respect to next month's industry returns, and confirming our results from Table 4. Importantly, we observe this relation after controlling for the cumulative industry return in the previous six months, which turns out not to be significant.

In sum, the results in this section suggest that the predictive ability in industry recommendations is not a manifestation of industry momentum.

### *6.2 Short-Term Price Pressure and Sentiment*

It may be that analysts do not possess any expertise in analyzing the prospects of different industries. Rather, analysts' industry recommendations create a "hype" or sentiment for some industries which is followed by a wide migration of investors to or away from those industries. In that case, the abnormal returns we observe merely reflect the short-term price pressure (either positive or negative) created by this migration. If that is the case, then the returns following industry recommendations should be short lived. That is, in the long-run prices will revert to fundamentals undoing the short-term price pressure. A similar phenomenon (in a different context) is documented in Ben-Rephael, Kandel, and Wohl (2011). They show that mutual-fund investors chase sentiment when switching between equity and bond funds. However, short-term returns obtained from this approach are reversed within one year.

To distinguish between this alternative explanation and the "industry expertise" hypothesis we examine whether the short-term abnormal returns obtained from following industry recommendations are reversed within one year. First, recall from Table 4 and Table 8 that the long-term returns following industry recommendations are smaller in magnitude compared to the one-month returns (and at times they become insignificant). These results suggest that some of the returns are indeed reversed. However, a formal test for reversal should directly examine the long-term returns, excluding the first month. To this end, we repeat the analysis presented in Table 4 and Table 8, skipping the first month. The results (untabulated, available upon request) for both the in-sample and out-of-sample analysis show either insignificant or significant and *positive* alphas for the long-short portfolios for all investment horizons. Thus, our tests do not identify any reversals in the period following the first month after portfolio formation.

Our interpretation of these tests along with the results in Table 4 is that the abnormal returns associated with industry recommendation may be partially attributed to price pressure. However, given that we cannot identify reversals explicitly, and since abnormal returns are still significant over the longer horizon (in Table 8 and in the in-sample analysis in Table 4), it seems that across-industry expertise still plays a role in explaining the results.

## 7 Conclusion

Industry analysis is an important aspect of sell-side research. It is likely composed of both analysts' ability to rank firms within an industry (carried out by firm-level analysts) as well as analysts' ability to rank industries relative to each other (largely carried out by strategy analysts). Our paper focuses on exploring analysts across-industry expertise and its relation to analysts' within-industry expertise. We perform our analysis using industry recommendation data that became available on IBES in 2002. This is a major output of analysts' research that has not been explored so far.

Institutional investors assign a high level of importance to analysts' industry expertise – as reflected in the *Institutional Investor Magazine* survey (cited in the Introduction), and in the awards granted to strategists based on their industry recommendations. Our results suggest that analysts do possess across-industry expertise as reflected in the investment value of their industry recommendations. Furthermore, the results highlight the importance of this new facet of analysts' outputs. As we show, industry recommendations incorporate information that is distinct from that conveyed by firm recommendations. Thus, combining the across- and within-industry expertise of analysts is beneficial. A caveat to these conclusions is that our results only pertain to brokerage houses that disclose industry recommendations. It could be that the disclosure decision is related to brokerage houses' efforts and abilities to analyze the prospects of industries. Consequently, these inferences may not extend to other brokerage houses.

Another important element of our study is that the analysis of industry recommendations enables us to better understand the meaning of firm recommendations. Firm-level analysts differ in their disclosures regarding the benchmark for their firm recommendations. Our empirical findings suggest that these differences are only partly reflected in the information contained in firm recommendations.

Being the first paper to study analysts' across-industry expertise as reflected in industry recommendations, several interesting questions remain. First, what is the source of investment value in industry recommendations? In particular, is there a link between industry recommendations and the subsequent investment decisions of either retail or institutional investors? Second, given the importance of industry knowledge, what is its role in analysts' compensation and reputation? Finally, it is interesting to explore the role of industry expertise in the careers and reputation of analysts. For example, given the importance that institutional investors assign to industry expertise it would be interesting to explore the relation between these expertise and achieving "All Star" status. These are questions to be addressed in future research.

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## Appendix I

To illustrate how IBES records industry recommendations we present a specific example. In January 2006, Bear Stearns published an analyst report on Apple (AAPL). We obtained this report from the Investext Plus database. The front page of the report shows that the analyst issued an 'outperform' recommendation for Apple. Additionally, the front page cites a 'market weight' recommendation for the IT hardware industry. This recommendation is taken from a periodic industry report prepared by a group of analysts at Bear Stearns.

IBES recorded these recommendations as follows:

| Ticker | RECDATS | BROKER | BTEXT/ETEXT | IRECCD |
|---|---|---|---|---|
| AAPL | 20060112 | BEAR | OUTPERFORM/MKTWT | 2 |

Note that the 'btext' item includes two words separated by a 'slash'. The text before the slash is the firm recommendation, whereas the text after the slash is the industry recommendation. Industry recommendations only appear in this item for brokers that include them in the front page of their firm reports.

Below, we present how we assign numeric values to the text depicting industry recommendations. We code optimistic industry recommendations as '1', neutral industry recommendations as '2', and pessimistic industry recommendations as '3'.

| **Optimistic (1)** | **Neutral (2)** | **Pessimistic (3)** |
|---|---|---|
| ACCUMULATE | CORE HOLD | AVOID |
| ABOVE AVERAGE | IN-LINE | CAUTIOUS |
| ACC | MARKET PERFORM | NEGATIVE |
| ACCUM | MARKETPERFORMER | REDUCE |
| ACCUMULATE | MARKETPERFRM | SELL |
| ADD | MKTWT | UNDERPERF. |
| ATTRACTIVE | MP | UNDERPERFORM |
| BUY | NEUTRAL | UNDERWT |
| OUTPERFORM | | |
| OVERWT | | |
| POSITIVE | | |
| STRONGBUY | | |

## Appendix II - Summary Statistics on the Global Industry Classification Standard (GICS)

This appendix presents summary statistics on each industry defined by GICS during our sample period (9/2002 – 12/2009). For each GICS, the table shows its corresponding industry name, the number of firms in the industry, the average market capitalization (in $M) and the average market-to-book ratio across firms in the industry, the number of brokerage houses (out of the 33 brokers in Table 1) that issue industry recommendations for this industry at any point during our sample period, the average number of brokerage houses which issue recommendations to this industry per month, the average number of recommendations issued to this industry per month, and the average level of these monthly industry recommendations. The latter is calculated as the average across all months in our sample period of the average monthly industry recommendation (which may include duplicate recommendations issued by the same broker in a given month). The number of firms in each industry is based on the number of firms in CRSP in 2009. The market capitalization and the market-to-book ratio are calculated based on 2009 and 2008 data, respectively. We assign industry recommendations a numeric value as follows: "optimistic"=1, "neutral"=2, "pessimistic"=3. The monthly industry recommendation is calculated as the average industry recommendation issued to the industry within the month.

| GICS | Industry_Name | # of firms | Avg. market cap | Avg. M/B | # of brokers covering | Avg. # of brokers issuing rec. per month | Avg. # of rec. per month | Avg. monthly industry rec. |
|---|---|---|---|---|---|---|---|---|
| 101010 | Energy Equipment & Services | 81 | 3754.50 | 0.59 | 11 | 3.20 | 13.27 | 1.28 |
| 101020 | Oil, Gas & Consumable Fuels | 292 | 5610.73 | 2.83 | 14 | 5.35 | 34.25 | 1.74 |
| 151010 | Chemicals | 89 | 3797.70 | 0.74 | 10 | 2.42 | 7.34 | 1.62 |
| 151020 | Construction Materials | 12 | 1602.13 | 0.49 | 4 | 0.35 | 0.52 | 1.78 |
| 151030 | Containers & Packaging | 22 | 1987.11 | 0.42 | 7 | 1.22 | 3.09 | 1.77 |
| 151040 | Metals & Mining | 138 | 3567.25 | 0.95 | 12 | 3.51 | 10.23 | 1.62 |
| 151050 | Paper & Forest Products | 18 | 1895.72 | 0.30 | 7 | 1.48 | 3.34 | 2.07 |
| 201010 | Aerospace & Defense | 68 | 4618.84 | 0.75 | 10 | 2.17 | 5.80 | 1.71 |
| 201020 | Building Products | 24 | 857.01 | 0.58 | 8 | 0.60 | 0.77 | 1.75 |
| 201030 | Construction & Engineering | 32 | 1428.12 | 0.69 | 11 | 0.99 | 2.13 | 1.68 |
| 201040 | Electrical Equipment | 99 | 1156.36 | 1.00 | 13 | 1.63 | 3.81 | 1.58 |
| 201050 | Industrial Conglomerates | 17 | 15565.78 | 0.61 | 7 | 1.08 | 1.73 | 1.65 |
| 201060 | Machinery | 121 | 2230.40 | 0.71 | 10 | 2.68 | 7.16 | 1.77 |
| 201070 | Trading Companies & Distributors | 30 | 934.12 | 0.60 | 8 | 1.06 | 1.55 | 1.80 |
| 202010 | Commercial Services & Supplies | 94 | 1062.96 | 0.80 | 13 | 3.13 | 9.45 | 1.78 |
| 202020 | Professional Services | 55 | 767.29 | 0.91 | 5 | 0.18 | 0.30 | 1.84 |
| 203010 | Air Freight & Logistics | 15 | 5904.04 | 1.20 | 6 | 1.11 | 2.50 | 1.71 |
| 203020 | Airlines | 22 | 1688.54 | 0.28 | 6 | 1.90 | 6.09 | 1.86 |
| 203030 | Marine | 27 | 410.35 | 0.30 | 6 | 0.55 | 0.91 | 2.09 |
| 203040 | Road & Rail | 36 | 4717.64 | 0.69 | 7 | 1.74 | 5.52 | 1.98 |
| 203050 | Transportation Infrastructure | 9 | 466.42 | 0.39 | 4 | 0.30 | 0.52 | 1.80 |
| 251010 | Auto Components | 40 | 1368.98 | 0.43 | 8 | 1.61 | 4.56 | 2.30 |
| 251020 | Automobiles | 8 | 12861.95 | 0.26 | 7 | 1.02 | 1.52 | 2.34 |
| 252010 | Household Durables | 73 | 1180.24 | 0.35 | 8 | 1.78 | 4.83 | 1.95 |
| 252020 | Leisure Equipment & Products | 26 | 727.91 | 0.50 | 10 | 0.74 | 1.06 | 1.76 |
| 252030 | Textiles, Apparel & Luxury Goods | 62 | 1343.44 | 0.75 | 9 | 1.32 | 3.26 | 2.02 |
| 253010 | Hotels, Restaurants & Leisure | 125 | 1913.11 | 0.60 | 14 | 4.01 | 15.27 | 1.84 |
| 253020 | Diversified Consumer Services | 41 | 1282.99 | 1.96 | 9 | 1.19 | 1.80 | 1.78 |
| 254010 | Media | 139 | 3011.21 | 0.37 | 11 | 4.45 | 18.97 | 1.96 |
| 255010 | Distributors | 11 | 860.56 | 0.42 | 5 | 0.26 | 0.26 | 2.14 |
| 255020 | Internet & Catalog Retail | 26 | 3493.56 | 1.38 | 11 | 1.80 | 3.22 | 1.63 |

## Appendix II – Cont.

| GICS | Industry_Name | # of firms | Avg. market cap | Avg. M/B | # of brokers covering | Avg. # of brokers issuing rec. per month | Avg. # of rec. per month | Avg. monthly industry rec. |
|---|---|---|---|---|---|---|---|---|
| 255030 | Multiline Retail | 17 | 5822.64 | 0.55 | 10 | 1.85 | 4.06 | 2.17 |
| 255040 | Specialty Retail | 121 | 2406.32 | 0.56 | 13 | 4.30 | 16.95 | 2.11 |
| 301010 | Food & Staples Retailing | 34 | 10888.92 | 0.71 | 8 | 1.88 | 4.28 | 1.87 |
| 302010 | Beverages | 35 | 8449.57 | 0.62 | 6 | 1.55 | 3.58 | 1.85 |
| 302020 | Food Products | 77 | 3724.15 | 0.79 | 7 | 2.01 | 5.15 | 2.15 |
| 302030 | Tobacco | 9 | 18444.96 | 4.35 | 5 | 0.52 | 1.14 | 1.63 |
| 303010 | Household Products | 13 | 20228.34 | 0.74 | 7 | 1.01 | 1.72 | 1.95 |
| 303020 | Personal Products | 34 | 1348.47 | 1.32 | 8 | 1.06 | 1.63 | 1.85 |
| 351010 | Health Care Equipment & Supplies | 154 | 2277.76 | 1.32 | 16 | 3.33 | 8.93 | 1.53 |
| 351020 | Health Care Providers & Services | 124 | 2323.75 | 0.87 | 12 | 4.07 | 18.17 | 1.69 |
| 351030 | Health Care Technology | 25 | 964.09 | 1.48 | 9 | 0.40 | 0.61 | 1.68 |
| 352010 | Biotechnology | 178 | 1296.45 | 2.46 | 14 | 3.99 | 11.67 | 1.54 |
| 352020 | Pharmaceuticals | 104 | 7546.38 | 1.60 | 12 | 3.44 | 9.69 | 1.59 |
| 352030 | Life Sciences Tools & Services | 57 | 1426.58 | 1.40 | 7 | 0.69 | 1.67 | 1.63 |
| 401010 | Commercial Banks | 399 | 1583.53 | 0.08 | 10 | 2.75 | 11.35 | 2.02 |
| 401020 | Thrifts & Mortgage Finance | 157 | 333.11 | 0.10 | 9 | 1.43 | 3.60 | 1.99 |
| 402010 | Diversified Financial Services | 39 | 11373.25 | 0.83 | 10 | 2.25 | 5.59 | 1.99 |
| 402020 | Consumer Finance | 23 | 3889.49 | 0.30 | 10 | 1.09 | 1.88 | 2.02 |
| 402030 | Capital Markets | 105 | 4541.15 | 0.66 | 10 | 2.45 | 8.18 | 1.87 |
| 403010 | Insurance | 142 | 4260.35 | 0.30 | 10 | 3.59 | 15.38 | 1.88 |
| 404010 | Real Estate -- Discontinued effective 04/28/2006 | | | | 6 | 1.68 | 8.53 | 2.33 |
| 404020 | Real Estate Investment Trusts (REITs) | 148 | 1974.60 | 0.38 | 6 | 1.28 | 7.16 | 2.28 |
| 404030 | Real Estate Management & Development | 35 | 1013.77 | 0.43 | 6 | 0.34 | 0.47 | 2.13 |
| 451010 | Internet Software & Services | 101 | 2688.59 | 1.10 | 12 | 3.20 | 7.61 | 1.56 |
| 451020 | IT Services | 90 | 2946.92 | 0.76 | 10 | 2.84 | 8.11 | 1.75 |
| 451030 | Software | 168 | 3677.52 | 1.31 | 16 | 4.32 | 15.73 | 1.70 |
| 452010 | Communications Equipment | 121 | 2993.19 | 0.72 | 14 | 3.82 | 11.91 | 1.77 |
| 452020 | Computers & Peripherals | 61 | 10149.39 | 0.81 | 14 | 2.97 | 8.28 | 1.81 |
| 452030 | Electronic Equipment, Instruments & Components | 144 | 966.18 | 0.73 | 10 | 3.02 | 7.58 | 1.82 |
| 452040 | Office Electronics | 3 | 3917.73 | 0.62 | 6 | 0.25 | 0.28 | 1.84 |
| 452050 | Semiconductor Equipment & Products -- Discontinued effective 04/30/2003. | | | | 11 | 0.59 | 5.84 | 1.76 |
| 453010 | Semiconductors & Semiconductor Equipment | 150 | 2559.40 | 0.80 | 12 | 4.13 | 21.14 | 1.73 |
| 501010 | Diversified Telecommunication Services | 70 | 5223.70 | 0.37 | 11 | 3.45 | 10.45 | 1.90 |
| 501020 | Wireless Telecommunication Services | 32 | 4739.27 | 0.46 | 13 | 2.89 | 7.03 | 1.88 |
| 551010 | Electric Utilities | 42 | 5802.72 | 0.35 | 7 | 2.45 | 8.99 | 2.28 |
| 551020 | Gas Utilities | 28 | 1890.83 | 0.51 | 7 | 1.06 | 2.34 | 2.06 |
| 551030 | Multi-Utilities | 27 | 5976.77 | 0.32 | 9 | 1.52 | 3.88 | 2.25 |
| 551040 | Water Utilities | 16 | 678.80 | 0.67 | 4 | 0.19 | 0.20 | 2.15 |
| 551050 | Independent Power Producers & Energy Traders | 14 | 2864.53 | 0.29 | 8 | 0.72 | 1.15 | 2.08 |

**Appendix III**

As we discussed in Section 2.3, when we draw a recommendation, the GICS industry to which we are associating that recommendation is incorrect roughly 22% of the time. This is a result of the fact that not all brokers use the GICS classification system. In this Appendix we illustrate the implications of these incorrect classifications, and explain how increasing the number of required recommendations reduces the noise associated with this problem. For this exercise assume that the unconditional distribution of industry recommendations comes from the statistics in Table 1, that is: 31% optimistic, 55% neutral, and 14% pessimistic.

Consider the probability of drawing an optimistic signal for industry *j* based on a single recommendation. This will occur when the single recommendation assigned to the industry *j*, $Rec_j$, equals 1, or:

$$\Pr(Ind_j = Optimistic) = \Pr(Rec_j = 1)$$

Since recommendations can be incorrectly mapped to industries, we need to distinguish between the recommendation as we map it using GICS, and the "true recommendation," which is the recommendation assigned to the industry given the issuing broker's classification system. In the example above, one could have observed an optimistic recommendation for industry *j* even when its true recommendation was neutral or pessimistic. We can then write,

$$\begin{aligned} \Pr(Rec_j=1) = {} & \Pr(Rec_j=1 \mid TrueRec_j=1)*\Pr(TrueRec_j=1)+ \\ & \Pr(Rec_j=1 \mid TrueRec_j=2)*\Pr(TrueRec_j=2)+ \\ & \Pr(Rec_j=1 \mid TrueRec_j=3)*\Pr(TrueRec_j=3) \qquad (1) \end{aligned}$$

If the GICS mapping were used by all brokers, then the last two terms would vanish, as the probability that we observe an optimistic recommendation when the true recommendation is not optimistic is zero, and we would trivially derive $\Pr(Rec_j=1 | TrueRec_j=1)=100\%$. That is, we would be left with $\Pr(Rec_j=1)=\Pr(TrueRec_j=1)$. Under the possibility of incorrect mappings, though, we need to rely on all these conditional probabilities to estimate the mapping error.

Let's explore the first such probability. If the true recommendation is '1,' then the probability of observing a recommendation of '1' is based on whether the GICS mapping matches the broker's mapping. If the mapping is correct (which happens 78% of the time), the reading is '1' with 100% certainty. If the mapping is incorrect (which happens 22% of the time), then the probability of drawing a recommendation of '1' can be approximated by the unconditional probability of having a recommendation of '1,' that is, 31%.[36] Let *MappingOk* denote the event that the GICS mapping is correct, and we can write:

$$\begin{aligned}\Pr(Rec_j\!=\!1|TrueRec_j\!=\!1) &= \Pr(\{Rec_j=1|TrueRec_j=1\}|\,MappingOk=1)*\Pr(MappingOk=1)+\\ &\quad \Pr(\{Rec_j=1|TrueRec_j=1\}|\,MappingOk=0)*\Pr(MappingOk=0)=\\ &\quad 1*0.78+0.31*0.22=0.8482,\end{aligned}$$

which means that, conditional on the analyst being optimistic about this particular GICS industry, only 84.82% of the readings will indicate optimism. Similarly, we obtain that $\Pr(Rec_j=1|TrueRec_j=2) = \Pr(Rec_j=1|TrueRec_j=3)=0.0682$ – that is, even when the true recommendation level is neutral or pessimistic, we still draw an optimistic level for the industry 6.82% of the time.

In sum, one sees optimistic industries 31% of the time, but only 26.29% ($\Pr(Rec_j=1 \mid TrueRec_j=1)*\Pr(TrueRec_j=1)=0.8482*0.31$) are true optimistic ones. The remaining, 3.75% and 0.96%, refer to industries that had, respectively, a truly neutral or pessimistic prospect but were incorrectly tagged as optimistic due to errors in GICS mappings. This amounts to 4.71%/31%=15.2% of the optimistic readings from single recommendations being incorrect. As for the industries tagged with a pessimistic tone, which happens 14% of the time, 2.65%, or 2.65%/14%=18.92% of them, are incorrectly set as pessimistic.

By increasing the number of required recommendations we can reduce these mapping errors with respect to optimistic and pessimistic readings. The idea is that if these errors are approximately independent (which would be the case in a large enough sample) then the probability of assigning the wrong recommendation level to an industry decreases with the number of sampled recommendations. The calculations when allowing for the cases in which we require at least two or three recommendations for an industry to be included in the portfolios are quite straightforward generalizations of those shown above (and are available upon request).

[36] We are assuming a large enough sample, so that we can consider drawing recommendations with replacement. Still the assumption that the distribution of recommendations when the mapping is incorrect is the same as the unconditional distribution of recommendations is a simplification. Given that an analyst tends to track companies that are similar to each other, returns on these tracked firms, as well as returns on their industries, will tend to be correlated. Thus, even when a recommendation is assigned to a different GICS than the one the analyst had in mind when publishing the recommendation, it is likely that the two industries are related, and thus their recommendations will be correlated as well. This suggests, for example, that $\Pr(\{Rec_j=1|TrueRec_j=1\}|MappingOk=0)$ can be higher than 31%. An examination of these conditional probabilities that adjusts for this additional correlation reveals, though, that the inferences here are not much affected.

Misclassifications still abound when industry signals are based on a combination of two recommendations. For example, 20.32% of industries classified as optimistic based on two recommendations are done so incorrectly. On the other hand, these misclassifications are almost completely eliminated when a 3-recommendations threshold is used; In this case, only 2.65% (1.40%) of optimistic (pessimistic) classifications are incorrect.

## Table 1 - Descriptive Statistics on Brokerage Houses and Industry Recommendations

**Panel A** presents summary statistics on the brokerage houses whose industry recommendations are available in IBES during our sample period (9/2002 – 12/2009). We report the broker name, the number of firms receiving recommendations from the brokerage house, the number of firm recommendations issued by each brokerage house, the average of such firm recommendations, the number of industries with available industry recommendations of each brokerage house, and the total number of industry recommendations issued by each brokerage house and available in IBES. When calculating the average firm recommendation, we assign firm recommendations a numeric value as follows: "strong buy" and "buy"=1, "hold"=2, "underperform" and "sell"=3. Industries are classified by the Global Industry Classification Standard (GICS). **Panel B** shows the number of industries covered by each of the sample's seven largest brokers for which we have industry recommendations. An industry is considered to be covered by a broker in a specific year if there is at least one industry recommendation being issued for that industry by the broker. **Panel C** reports the distribution of the industry recommendations levels over the years for all brokers. We assign industry recommendations a numeric value as follows: "optimistic"=1, "neutral"=2, "pessimistic"=3. **Panel D** shows the average industry recommendation for each broker and each year of our sample.

### **Panel A** – Summary Statistics on Brokerage Houses

| Broker | # of firms covered | Total # of firm recommendations | Avg. firm recommendation | # of industries with industry recommendations | Total # of industry recommendations |
|---|---|---|---|---|---|
| Goldman Sachs | 1904 | 10163 | 1.89 | 70 | 9985 |
| Morgan Stanley | 1799 | 7118 | 1.88 | 70 | 7116 |
| CSFB | 2145 | 9039 | 1.73 | 68 | 6678 |
| Bear Stearns | 1567 | 5396 | 1.75 | 66 | 5366 |
| Lehman Bros. | 1754 | 5291 | 1.76 | 65 | 5250 |
| CIBC | 1304 | 3756 | 1.81 | 57 | 3751 |
| Barclays | 1072 | 1885 | 1.70 | 63 | 1831 |
| Sanders M. Harris | 324 | 984 | 1.52 | 37 | 373 |
| Jonhson Rice | 231 | 857 | 1.24 | 17 | 360 |
| CE Unterberg | 468 | 1162 | 1.59 | 19 | 256 |
| Cai Cheuvreux | 21 | 118 | 1.82 | 13 | 69 |
| Rochdals | 85 | 140 | 1.60 | 18 | 54 |
| Forun | 29 | 48 | 1.42 | 9 | 46 |
| HSBC | 299 | 805 | 1.80 | 11 | 35 |
| Capstone | 101 | 336 | 1.43 | 15 | 29 |
| Varicorp | 44 | 67 | 1.46 | 6 | 19 |
| WHENTRAD | 36 | 50 | 1.64 | 5 | 16 |
| Wasserman | 11 | 15 | 1.20 | 6 | 15 |
| Summit Analytic | 15 | 37 | 2.68 | 2 | 13 |
| US Trust | 8 | 9 | 2.33 | 1 | 9 |
| Cokerpal | 33 | 106 | 1.24 | 3 | 9 |
| Haywood | 16 | 36 | 1.39 | 3 | 8 |
| CJS | 185 | 455 | 1.51 | 4 | 5 |
| Thomas Weisel | 1074 | 2668 | 1.66 | 4 | 4 |
| Samuel Ramirez | 18 | 19 | 1.21 | 3 | 4 |
| Allaria Ledesma | 3 | 8 | 1.38 | 2 | 3 |
| Enskilda | 6 | 12 | 1.67 | 2 | 2 |
| Merrill Lynch | 2829 | 12183 | 1.75 | 1 | 2 |
| Anderson Strudwick | 10 | 11 | 1.00 | 2 | 2 |
| Octagon | 2 | 3 | 1.33 | 1 | 2 |
| Advest | 183 | 356 | 1.44 | 1 | 1 |
| Janco | 128 | 382 | 1.35 | 1 | 1 |
| Caris | 381 | 1206 | 1.48 | 1 | 1 |

**Table 1 (*continued*)**

**Panel B** – Industry Coverage by Broker and by Year for the Seven Largest Brokers

| Broker | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 |
|---|---|---|---|---|---|---|---|---|
| Goldman Sachs | 51 | 54 | 53 | 57 | 65 | 66 | 66 | 64 |
| Morgan Stanley | 49 | 59 | 55 | 56 | 61 | 61 | 61 | 57 |
| CSFB | 53 | 57 | 57 | 58 | 61 | 64 | 29 | - |
| Bear Stearns | 48 | 54 | 49 | 53 | 57 | 56 | 45 | - |
| Lehman Bros. | 44 | 56 | 53 | 56 | 60 | 58 | 42 | - |
| CIBC | 43 | 43 | 40 | 40 | 41 | 41 | 12 | 4 |
| Barclays | - | - | - | - | - | - | 62 | 60 |
| Number of GICS Industries | 59 | 62 | 62 | 64 | 67 | 67 | 68 | 68 |

**Panel C** – Distribution of Industry Recommendations by Year for All Brokers in Sample

| Industry Recommendation (%) | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | Overall |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 33.92 | 31.62 | 33.33 | 32.27 | 31.26 | 28.58 | 28.50 | 35.22 | 31.71 |
| 2 | 52.17 | 51.01 | 52.59 | 52.84 | 54.97 | 59.09 | 59.70 | 55.72 | 54.53 |
| 3 | 13.90 | 17.37 | 14.08 | 14.89 | 13.77 | 12.34 | 11.80 | 9.06 | 13.76 |

**Panel D** – Average Industry Recommendations by Broker and Year for the Seven Largest Brokers

| Broker | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | Overall |
|---|---|---|---|---|---|---|---|---|---|
| Goldman Sachs | 1.89 | 1.94 | 1.93 | 2.02 | 1.87 | 1.89 | 1.91 | 1.75 | 1.88 |
| Morgan Stanley | 1.95 | 2.02 | 1.90 | 1.99 | 1.88 | 1.77 | 1.84 | 1.71 | 1.88 |
| CSFB | 1.78 | 1.91 | 1.79 | 1.71 | 1.88 | 1.86 | 1.79 | - | 1.83 |
| Bear Stearns | 1.66 | 1.93 | 1.78 | 1.91 | 1.84 | 1.96 | 1.90 | - | 1.85 |
| Lehman Bros. | 1.85 | 1.75 | 1.78 | 1.67 | 1.72 | 1.70 | 1.82 | - | 1.74 |
| CIBC | 1.75 | 1.72 | 1.71 | 1.77 | 1.74 | 1.78 | 1.65 | 1.64 | 1.74 |
| Barclays | - | - | - | - | - | - | 1.73 | 1.74 | 1.73 |

## Table 2 – Determinants of Industry Recommendations

This table reports the results of estimating logistic models of the probabilities of issuing an optimistic or pessimistic industry recommendation during our sample period (9/2002-12/2009). Reiterations during a month are excluded. The independent variables are as follows: **Industry_Size** is the natural logarithm of the aggregate market capitalization of the industry at the beginning of the month, **MB** is the industry weighted average of the market-to-book ratio, **Profit** is the industry weighted average of net income margin, **R&D** is the industry weighted average of the R&D divided by sales, **Capex** is the industry weighted average of the capital expenditures divided by sales. Accounting variables are measured at the beginning of the year. All weighted averages are by the firm market-capitalization at the beginning of the year in which a recommendation is issued. **IND_RET** is the return to an industry index in the previous quarters (up to three quarters back). **MKT_RET** is the market return in the previous quarters (up to three quarters back). **TOTAL_IPOSEO** is the total IPO/SEO proceeds in the industry during the year preceding the recommendation. **AVG_IPOSEO** is the average IPO/SEO proceeds in the industry during the year preceding the recommendation. **IPOSEO_PCT** is the percentage of IPO/SEO proceeds in an industry underwritten by the issuing broker during the two years preceding the recommendation, out of all IPO/SEO proceeds underwritten by the same broker during that time period. **Recession** is a dummy variable and takes value of 1 if a recommendation is issued between 12/2007 and 6/2009. **Cyclical** is a dummy variable and takes value of 1 if a recommendation is issued to materials, industrials and IT industries. Marginal effects are reported at medians. In both specifications we control for broker fixed-effects. Robust standard errors (in parentheses) are calculated after clustering at the broker-industry level. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

| | Prob(Ind Rec=Optimistic) | | Prob(Ind Rec=Pessimistic) | |
|---|---|---|---|---|
| | Coefficient | Marginal Effects | Coefficient | Marginal Effects |
| Industry_ Size | -0.0206 | -0.0051 | -0.0921 | -0.0078 |
| | (0.057) | | (0.079) | |
| MB | -0.0022** | -0.0005 | 0.0018** | 0.0002 |
| | (0.001) | | (0.001) | |
| Profit | 0.9802* | 0.2419 | -2.2107*** | -0.1867 |
| | (0.506) | | (0.747) | |
| R&D | 3.8978** | 0.9621 | -8.9194*** | -0.7535 |
| | (1.637) | | (2.135) | |
| Capex | 0.9731*** | 0.1386 | -0.9139* | -0.1151 |
| | (0.325) | | (0.495) | |
| IND_RETt-1 | 1.3603*** | 0.2402 | -0.9928** | -0.0772 |
| | (0.290) | | (0.431) | |
| IND_RETt-2 | 0.6947*** | 0.3357 | -1.5756*** | -0.0839 |
| | (0.253) | | (0.400) | |
| IND_RETt-3 | 0.1838 | 0.1715 | -0.6330* | -0.1331 |
| | (0.277) | | (0.352) | |
| MKT_RETt-1 | 0.3746 | 0.0454 | -1.8627*** | -0.0535 |
| | (0.246) | | (0.389) | |
| MKT_RETt-2 | -0.4463* | 0.0925 | -0.1666 | -0.1573 |
| | (0.247) | | (0.401) | |
| MKT_RETt-3 | 0.5615 | -0.1102 | -1.3627 | -0.0141 |
| | (1.695) | | (2.469) | |
| Recession | -0.0046 | -0.0011 | -0.4836** | -0.0289 |
| | (0.137) | | (0.215) | |
| Cyclical | 0.2635** | 0.0656 | -0.4020** | -0.0336 |
| | (0.126) | | (0.167) | |
| Cyclical*Recession | -0.4223** | -0.1004 | 0.3543 | 0.0345 |
| | (0.208) | | (0.362) | |
| TOTAL_IPOSEO | 0.1140** | 0.0281 | -0.0139 | -0.0012 |
| | (0.057) | | (0.077) | |
| AVG_IPOSEO | -0.1758** | -0.0434 | 0.0458 | 0.0038 |
| | (0.077) | | (0.107) | |
| IPOSEO_PCT | 0.6752 | 0.1667 | -1.1361 | -0.0960 |
| | (1.952) | | (1.613) | |
| Observations | 13,588 | | 13,392 | |

**Table 3 – Summary Statistics on the Industry Recommendation Portfolios**

This table reports summary statistics on the industry recommendation portfolios during our sample period (9/2002-12/2009). Our industry portfolios are constructed for each month based on consensus recommendations. A consensus recommendation is defined as the average industry recommendation within the month. In each month we refer to the consensus recommendation for an industry as "optimistic" if this consensus is less than or equal 1.5. We refer to the consensus recommendation as "pessimistic" if it is greater than or equal to 2.5. In all other cases, we refer to the consensus as "neutral." We then construct three industry portfolios based on consensus changes for each month. Portfolio UI in month *t* consists of all industries that were upgraded to "optimistic" during month *t*-1, Portfolio DI consists of all industries that were downgraded to "pessimistic" during month *t*-1, and Portfolio NI consists of all industries that were either upgraded or downgraded into the "neutral" consensus during month *t*-1. Panel A describes basic characteristics about the portfolio formation: the number of months each portfolio is defined over; the average monthly consensus recommendation for all the industries that are part of the portfolio; the average number of industries included in each portfolio per month; the average number of firms (across all industries) in each portfolio; and the total number of different industries which ever enter into the portfolio. Panel B shows various portfolio returns. Industry return is defined as the value-weighted return across all CRSP firms in the relevant month. The monthly return for portfolios UI, NI, and DI is the equal weighted return of all industries in the relevant portfolio. "UI minus DI" is the self financing investment strategy of buying the industry recommendation portfolio UI and shorting the industry recommendation portfolio DI.

**Panel A – Portfolio Formation Characteristics**

| Industry Recommendation Portfolio | # of Months | Ave. Monthly Consensus Rec. | Ave. # of Industries per month | Ave. # of Firms | # of industries |
|---|---|---|---|---|---|
| UI | 87 | 1.29 | 5.51 | 667.55 | 65 |
| NI | 87 | 1.92 | 10.42 | 1077.11 | 68 |
| DI | 65 | 2.77 | 2.83 | 294.98 | 47 |

**Panel B – Industry Recommendation Portfolio Returns**

| Industry Recommendation Portfolio | Raw Monthly Return | | | | | Cumulative Returns | | |
|---|---|---|---|---|---|---|---|---|
| | t-2 | t-1 | t | t+1 | t+2 | 3 months (t, t+2) | 6 months (t,t+5) | 12 months (t,t+11) |
| UI | 0.0115 | 0.0133 | 0.0132 | 0.009 | 0.0036 | 0.0262 | 0.0578 | 0.0930 |
| p-value | 0.0488 | 0.035 | 0.0182 | 0.116 | 0.5787 | 0.0339 | 0.0018 | 0.0007 |
| NI | 0.0067 | 0.0068 | 0.0121 | 0.0095 | 0.0096 | 0.0313 | 0.0643 | 0.0916 |
| p-value | 0.2477 | 0.2405 | 0.0243 | 0.1006 | 0.0785 | 0.0042 | 0.0005 | 0.0008 |
| DI | 0.0058 | -0.002 | 0.0009 | 0.01 | 0.0112 | 0.0237 | 0.0533 | 0.0604 |
| p-value | 0.5108 | 0.8176 | 0.9223 | 0.1671 | 0.182 | 0.1765 | 0.0504 | 0.0830 |
| UI minus DI | 0.0024 | 0.0130 | 0.0136 | -0.002 | -0.006 | 0.0065 | 0.0171 | 0.0442 |
| p-value | 0.7063 | 0.0491 | 0.0175 | 0.6543 | 0.2757 | 0.4843 | 0.2078 | 0.0222 |

**Table 4 - In-Sample/Out-of-Sample Alphas of Industry Recommendation Portfolios**

This table reports the in-sample alphas (Panel A) and the out-of-sample alphas (Panel B) of the industry recommendation portfolios during our sample period (9/2002-12/2009). The in-sample/out-of-sample tests are performed on each portfolio return in month *t* by using Fama-French four-factor model. Our industry portfolios are constructed for each month based on the consensus recommendations. A consensus recommendation is defined as the average industry recommendation within the month. In each month we refer to the consensus recommendation for an industry as "optimistic" if this consensus is less than or equal 1.5. We refer to the consensus recommendation as "pessimistic" if it is greater than or equal to 2.5. In all other cases, we refer to the consensus as "neutral." We then construct three industry portfolios for each month. Portfolio UI in month *t* consists of all industries that were upgraded to "optimistic" during month *t*-1, Portfolio DI consists of all industries that were downgraded to "pessimistic" during month *t*-1, and Portfolio NI consists of all industries that were either upgraded or downgraded into the "neutral" consensus during month *t*-1. Once it enters a portfolio, an industry stays in it for "n" months or until it is upgraded or downgraded. "n" is equal to 1 month, 3 months, 6 months, or 12 months. Industry return is defined as the value-weighted return across all CRSP firms in the relevant month. The monthly return for portfolios UI, NI, and DI is the equal weighted return of all industries in the relevant portfolio. "UI minus DI" is the self financing investment strategy of buying the industry recommendation portfolio UI and shorting the industry recommendation portfolio DI.

**Panel A –In-Sample Alphas on Industry Recommendation Portfolios**

| Industry Recommendation Portfolio | 1 month | 3 months | 6 months | 12 months |
|---|---|---|---|---|
| UI | 0.0054 | 0.0032 | 0.0032 | 0.0035 |
| p-value | 0.0204 | 0.0246 | 0.0183 | 0.0110 |
| NI | 0.0041 | 0.0017 | 0.0018 | 0.0017 |
| p-value | 0.0195 | 0.0679 | 0.0367 | 0.0432 |
| DI | -0.0110 | -0.0057 | -0.0058 | -0.0052 |
| p-value | 0.0060 | 0.1003 | 0.0520 | 0.0837 |
| UI minus DI | 0.0147 | 0.0069 | 0.0071 | 0.0068 |
| p-value | 0.0032 | 0.0818 | 0.0397 | 0.0561 |

**Panel B – Out-of-Sample Alphas on Industry Recommendation Portfolios**

| Industry Recommendation Portfolio | 1 month | 3 months | 6 months | 12 months |
|---|---|---|---|---|
| UI | 0.0059 | 0.0017 | 0.0020 | 0.0023 |
| p-value | 0.0088 | 0.3158 | 0.1492 | 0.0815 |
| NI | 0.0014 | 0.0003 | 0.00037 | 0.0003 |
| p-value | 0.4054 | 0.7811 | 0.7185 | 0.7901 |
| DI | -0.0086 | -0.0036 | -0.0040 | -0.0026 |
| p-value | 0.0453 | 0.2893 | 0.1586 | 0.3856 |
| UI minus DI | 0.0138 | 0.0031 | 0.0040 | 0.0028 |
| p-value | 0.0030 | 0.4059 | 0.2048 | 0.3996 |

**Table 5 - Distribution of Industry Recommendations and Firm Recommendations**

This table reports the distribution of firm recommendations within industry recommendation levels during our sample period (9/2002 – 12/2009). Industry recommendations are coded as follows: "optimistic"=1, "neutral"=2, "pessimistic"=3. Firm recommendations are coded as follows: "strong buy" and "buy"=1, "hold"=2, "underperform" and "sell"=3.

| Industry Recommendation | Firm Recommendation | Frequencies | % of total | % of industry |
|---|---|---|---|---|
| 1 | 1 | 5456 | 13.33% | 42.04% |
| 1 | 2 | 5844 | 14.28% | 45.03% |
| 1 | 3 | 1678 | 4.10% | 12.93% |
| Ave. (1) | 1.71 | | 31.71% | 100.00% |
| 2 | 1 | 7485 | 18.29% | 33.54% |
| 2 | 2 | 11532 | 28.18% | 51.68% |
| 2 | 3 | 3298 | 8.06% | 14.78% |
| Ave. (2) | 1.81 | | 54.53% | 100.00% |
| 3 | 1 | 1487 | 3.63% | 26.41% |
| 3 | 2 | 2879 | 7.04% | 51.14% |
| 3 | 3 | 1264 | 3.09% | 22.45% |
| Ave. (3) | 1.96 | | 13.76% | 100.00% |
| *p-values* | | | | |
| Ave (1) = Ave (2) | <.0001 | | | |
| Ave (2) = Ave (3) | <.0001 | | | |

**Table 6 – Analysts' disclosure about the meaning of firm recommendations**

This table reports information regarding the nature of firm recommendations, as it is disclosed by the brokerage houses. We include the 20 largest brokers in terms of the number of recommendations they issued during our sample period (9/2002-12/2009). In addition to the brokerage name and the percentage of recommendations, we indicate whether the recommendations are benchmarked to the industry. We also include an example of the original remark about the adopted benchmark by the brokerage house. These remarks are taken from brokerage disclosures included in their reports.

| # | **Brokerage House** | **% of recs.** | **Benchmark is Industry?** | **Remarks about the benchmark** |
|---|---|---|---|---|
| 1 | Argus Research | 1.46% | No | "We will generally rate a stock a buy if, in our view, the forecast risk-adjusted return on the stock is greater than the forecast return on the market." |
| 2 | Banc of America | 1.74% | No | "The rating system is based on a stock's forward -12-month expected total return (price appreciation plus dividend yield)." |
| 3 | Bear Stearns | 2.11% | Yes | "Stock's expected performance vs. analyst's industry coverage for the next 12 months." |
| 4 | CIBC | 1.52% | Yes | "Stock's expected performance vs. the sector for the next 12-18 months." |
| 5 | CSFB | 3.64% | Yes | "Stock's expected total return vs. the industry for the next 12 months." |
| 6 | Deutsche Bank | 2.04% | No | "Buy: total return expected to appreciate 10% or more over a 12-month period." |
| 7 | Friedman Billing | 1.51% | Yes | Performance "relative to similar companies within its industry over the next 12-18 months." |
| 8 | Goldman Sachs | 4.12% | Yes | "Our ratings reflect expected stock price performance relative to each analyst's coverage universe." |
| 9 | Jefferies and Co. | 1.55% | No | "Buy: describes stocks that we expect to provide a total return of 15% or more within a 12-month period." |
| 10 | JP Morgan | 3.05% | Yes | "Overweight: Over the next six to twelve months, we expect this stock will outperform the average total return of the stocks in the analyst's (or the analyst's team's) coverage universe." |
| 11 | Lehman Brothers | 2.16% | Yes | "Stock's performance vs. the industry for a 12 month investment horizon" |
| 12 | Merrill Lynch | 4.45% | No | "Based on stock's expected total return within a 12 month period." |
| 13 | Morgan Stanley | 2.77% | Yes | "Stock's total return vs. analyst's coverage on a risk-adjusted basis, for the next 12-18 months." |
| 14 | Raymond James | 1.76% | No | Performance "relative to the market index over the next 12 months." |
| 15 | RBC | 1.39% | Yes | "The rating assigned to a particular stock represents solely the analyst's view of how that stock will perform over the next 12 months relative to the analyst's sector" |
| 16 | Sidoti | 1.37% | No | "Buy implies at least 25% upside over a 12-month period." |
| 17 | Smith Barney | 3.34% | Yes | "Stock's performance vs. the analyst's industry coverage for the coming 12-18 months." |
| 18 | UBS | 3.48% | No | "The UBS rating system begins with the analyst determining the forecast stock return over the next 12 months. The forecast stock return relative to a predefined hurdle rate determines the Recommendation (Buy, Neutral, or Sell). This hurdle rate is set on either side of an unbiased estimate of the market's return over the next 12 months." |
| 19 | US Bancorp Piper Jaffray | 1.96% | No | Performance "relative to the market index over the next 12 months." |
| 20 | Wachovia | 1.73% | No | Performance "relative to the market over the next 12 months." |

## Table 7 – Pseudo-Industry Recommendations

This table reports tests on the monthly pseudo-industry recommendations during our sample period (9/2002-12/2009). We use three different ways to define pseudo-industry recommendations. ***All Brokers*** defines monthly pseudo-industry recommendations as the value-weighted firm recommendations issued by all brokers in IBES within a month and an industry. ***Industry Benchmarkers*** defines monthly pseudo-industry recommendations as the value-weighted firm recommendations issued by 10 brokers out of 20 largest brokers in the IBES which use the sector benchmark for firm recommendations. ***Market Benchmarkers*** defines monthly pseudo-industry recommendations as the value-weighted firm recommendations issued by 10 brokers out of 20 largest brokers in the IBES which use the market benchmark for firm recommendations. Panel A presents summary statistics of each type of pseudo-industry recommendations. Panel B presents the correlation among the three pseudo-industry recommendations and the true industry recommendation. Panel C shows the in-sample/out-of-sample alphas of portfolios of upgraded industries (PUI), neutral industries (PNI) and downgraded industries (PDI) constructed based on pseudo industry recommendations. The portfolios are constructed in a manner similar to the portfolios UI, NI and DI in Table 3, except that now the industry outlook is expressed by pseudo industry recommendations rather than the true industry recommendations.

**Panel A – Summary Statistics**

| | Pseudo-industry recommendation | | |
|---|---|---|---|
| | N | Average | STD |
| All brokers | 5598 | 1.6227 | 0.3316 |
| 10 industry benchmarkers | 4999 | 1.7143 | 0.4392 |
| 10 industry market benchmarkers | 5040 | 1.6180 | 0.4475 |
| Real-industry recommendation | 4476 | 1.8541 | 0.4941 |

**Panel B – Correlation Matrix**

| | Pseudo Ind. Rec. (All brokers) | Pseudo Ind. Rec. (Industry Benchmarkers) | Pseudo Ind. Rec. (Market Benchmarkers) | Real-industry Recs |
|---|---|---|---|---|
| Pseudo Ind. Rec. (All brokers) | 1 | | | |
| Pseudo Ind. Rec. (Industry Benchmarkers) | 0.5207 | 1 | | |
| Pseudo Ind. Rec. (Market Benchmarkers) | 0.4887 | 0.1191 | 1 | |
| Real Industry Recs | 0.1582 | 0.1432 | 0.1054 | 1 |

**Panel C –In-Sample/ Out-of-Sample Alphas**

| | In-Sample Alphas | | | Out-of-Sample Alphas | | |
|---|---|---|---|---|---|---|
| Portfolio | All Brokers | Industry Benchmarkers | Market Benchmarkers | All Brokers | Industry Benchmarkers | Market Benchmarkers |
| PUI | 0.0031 | 0.0024 | 0.0042 | 0.0026 | 0.0013 | 0.0036 |
| p-value | 0.1088 | 0.2368 | 0.0109 | 0.1470 | 0.5689 | 0.0166 |
| PNI | -0.0007 | 0.0008 | -0.0010 | 0.0006 | 0.0012 | -0.0024 |
| p-value | 0.7372 | 0.6065 | 0.4760 | 0.7365 | 0.4615 | 0.1525 |
| PDI | 0.0076 | 0.0018 | -0.0129 | 0.0002 | -0.0020 | -0.0019 |
| p-value | 0.1763 | 0.7299 | 0.0522 | 0.9785 | 0.6775 | 0.7903 |
| PUI minus PDI | -0.0046 | -0.0011 | 0.0167 | -0.0046 | 0.0025 | 0.0013 |
| p-value | 0.5079 | 0.8671 | 0.0138 | 0.7107 | 0.8178 | 0.5032 |

**Table 8 – In-Sample/Out-of-Sample Alphas of Portfolios Sorted by Firm and Industry Recommendations**

This table presents the performance of portfolios sorted by both firm recommendations and industry consensus recommendations during our sample period (9/2002-12/2009). For each month *t*, firms are first sorted based on the consensus industry recommendation, and then are sorted based on firm recommendations (upgrades and downgrades). Industry recommendation portfolios are constructed as follows: for each month the consensus industry recommendation is defined as the average industry recommendation within the month. In each month we refer to the consensus recommendation for an industry as "optimistic" if this consensus is less than or equal 1.5. We refer to the consensus recommendation as "pessimistic" if it is greater than or equal to 2.5. In all other cases, we refer to the consensus as "neutral." We then construct three industry portfolios for each month. Portfolio UI in month *t* consists of all industries that were upgraded to "optimistic" during month *t*-1, Portfolio DI consists of all industries that were downgraded to "pessimistic" during month *t*-1, and Portfolio NI consists of all industries that were either upgraded or downgraded into the "neutral" consensus during month *t*-1. Firm recommendation portfolios are constructed as follows: For each stock, we count the number of upgrades and number of downgrades that the stock received in month *t*-1. Portfolio UF includes stocks with a larger number of upgrades than downgrades, while portfolio DF includes stocks with more downgrades. Once it enters a portfolio, a firm will stay in the portfolio for "n" months or until its firm recommendation/industry recommendation is changed. "n" is equal to 1 month, 3 months, 6 months, or 12 months. (UI,UF) refers to the portfolio of firms which belong to both industry recommendation portfolio UI and firm recommendation portfolio UF. (DI,DF) refers to the portfolio of firms which belongs to both industry recommendation portfolio DI and firm recommendation portfolio DF. "(UI,UF) minus (DI,DF)" refers to the investment strategy of buying portfolio (UI,UF) and shorting portfolio (DI,DF). Out-of-sample tests are performed on the portfolio return in month *t* by using Fama-French four-factor model.

**Panel A – In-Sample Alphas**

| | 1 month | | 3 months | | 6 months | | 12 months | |
|---|---|---|---|---|---|---|---|---|
| | Firm Recommendation Portfolios | | Firm Recommendation Portfolios | | Firm Recommendation Portfolios | | Firm Recommendation Portfolios | |
| Industry Recommendation Portfolios | UF | DF | UF | DF | UF | DF | UF | DF |
| UI | 0.0128 | 0.0101 | 0.0065 | 0.0080 | 0.0049 | 0.0069 | 0.0058 | 0.0067 |
| p-value | 0.0048 | 0.0371 | 0.0247 | 0.0173 | 0.0855 | 0.0400 | 0.0390 | 0.0470 |
| NI | 0.0090 | 0.0018 | 0.0073 | -0.0008 | 0.0067 | -0.0002 | 0.0060 | -0.0002 |
| p-value | 0.0014 | 0.4823 | 0.0000 | 0.6012 | 0.0000 | 0.8739 | 0.0001 | 0.9133 |
| DI | -0.0078 | -0.0232 | -0.0081 | -0.0129 | -0.0112 | -0.0188 | -0.0102 | -0.0184 |
| p-value | 0.2332 | 0.0030 | 0.0653 | 0.0270 | 0.0029 | 0.0003 | 0.0052 | 0.0001 |
| UI minus DI | 0.0208 | 0.0269 | 0.0130 | 0.0155 | 0.0147 | 0.0204 | 0.0146 | 0.0197 |
| p-value | 0.0216 | 0.0070 | 0.0378 | 0.0132 | 0.0068 | 0.0005 | 0.0050 | 0.0004 |
| (UI,UF) minus (DI,DF) | 0.0373 | | 0.0177 | | 0.0222 | | 0.0227 | |
| p-value | 0.0003 | | 0.0173 | | 0.0007 | | 0.0002 | |

**Table 8 (*continued*)**

**Panel B – Out-of-Sample Alphas**

| Industry Recommendation Portfolios | 1 month Firm Recommendation Portfolios | | 3 months Firm Recommendation Portfolios | | 6 months Firm Recommendation Portfolios | | 12 months Firm Recommendation Portfolios | |
|---|---|---|---|---|---|---|---|---|
| | UF | DF | UF | DF | UF | DF | UF | DF |
| UI | 0.0144 | 0.0150 | 0.0057 | 0.0096 | 0.0039 | 0.0084 | 0.0049 | 0.0079 |
| p-value | 0.0006 | 0.0053 | 0.0350 | 0.0111 | 0.1310 | 0.0243 | 0.0485 | 0.0330 |
| NI | 0.0050 | -0.0006 | 0.0040 | -0.0021 | 0.0036 | -0.0011 | 0.0030 | -0.0015 |
| p-value | 0.0622 | 0.8342 | 0.0252 | 0.2894 | 0.0210 | 0.5355 | 0.0477 | 0.4197 |
| DI | -0.0065 | -0.0169 | -0.0046 | -0.0119 | -0.0074 | -0.0157 | -0.0067 | -0.0137 |
| p-value | 0.3330 | 0.0246 | 0.2840 | 0.0873 | 0.0463 | 0.0037 | 0.0566 | 0.0046 |
| UI minus DI | 0.0233 | 0.0284 | 0.0083 | 0.0160 | 0.0095 | 0.0189 | 0.0097 | 0.0163 |
| p-value | 0.0113 | 0.0061 | 0.1393 | 0.0225 | 0.0499 | 0.0014 | 0.0033 | 0.0020 |
| (UI,UF) minus (DI,DF) | 0.0330 | | 0.0161 | | 0.0183 | | 0.0171 | |
| p-value | 0.0007 | | 0.0393 | | 0.0031 | | 0.0020 | |

## Table 9 – Robustness for Momentum

This table reports the robustness of the investment value of industry recommendation portfolios after controlling for industry momentum. For each month *t* during our sample period (9/2002-12/2009), we construct three momentum portfolios based on the cumulative industry returns in the previous six months. Momentum portfolio MOM1 contains the top 15% of industries with the highest past returns, and momentum portfolio MOM3 contains the bottom 15% of industries with the lowest past returns. Industry return is defined as the value-weighted return across all CRSP firms in the relevant industry in month *t*. **Panel A** reports the overlap between industry momentum portfolios and industry recommendation portfolios. **Panel B** reports the out-of-sample alphas of momentum portfolios. The monthly return for the momentum portfolios is the equal weighted return of all industries in the relevant portfolio. "MOM1 minus MOM3" is the self financing investment strategy of buying the industry momentum portfolio MOM1 and shorting the industry momentum portfolio MOM3. "UI minus DI" is the self financing investment strategy of buying the industry recommendation portfolio UI and shorting the industry recommendation portfolio DI. The in-sample/out-of-sample tests are performed on the portfolio return in month t by using Fama-French four-factor model. **Panel C** reports the in-sample/out-of-sample alphas of industry recommendation portfolios net of momentum portfolios. More specifically, industries which belong to momentum portfolio MOM1 (MOM3) are excluded from industry recommendation portfolio UI (DI). **Panel D** reports the results of analyzing the performance of industry recommendation portfolios by using Fama-Macbeth regressions. The dependent variable is the industry recommendation portfolio return in month *t*. Details on the construction of industry recommendation portfolios are discussed in table 3. The independent variables are as follows**: Port** takes value of 1 (2 or 3) if an industry belongs to industry recommendation portfolio UI (NI or DI) in month t, **Ind_Rec** is the consensus industry recommendation (i.e. the average of all industry recommendations) in month *t-1*, **Firm Size** is the value-weighted average firm size in an industry in month *t-1*, **MB** is value weighted market-to-book ratio in an industry in previous year, **Market_Beta** is the an industry's market beta estimated using previous 60-month return data, and **Past_Ind_Ret** is the cumulative industry return from month t-6 to month t-1. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

**Panel A - The overlap between industry momentum portfolios and industry recommendation portfolios**

| Industry recommendation Portfolio | Momentum Portfolio | No. of Industries | % of total (conditional) |
|---|---|---|---|
| UI | MOM1 | 87 | 17.94% |
| UI | MOM2 | 340 | 70.10% |
| UI | MOM3 | 58 | 11.96% |
| | | 485 | 100.00% |
| NI | MOM1 | 119 | 12.98% |
| NI | MOM2 | 652 | 71.10% |
| NI | MOM3 | 146 | 15.92% |
| | | 917 | 100.00% |
| DI | MOM1 | 19 | 10.33% |
| DI | MOM2 | 127 | 69.02% |
| DI | MOM3 | 38 | 20.65% |
| | | 184 | 100.00% |

**Table 9 (*continued*)**

**Panel B –Four Factor Alphas on Momentum Portfolios**

| Momentum Portfolio | In-Sample Alpha | Out-of-Sample Alpha |
|---|---|---|
| MOM1 | 0.0027 | -0.0027 |
| *p-value* | 0.2582 | 0.3056 |
| MOM2 | 0.0004 | 0.1132 |
| *p-value* | 0.6385 | 0.9101 |
| MOM3 | 0.0003 | 0.0044 |
| *p-value* | 0.9106 | 0.1337 |
| MOM1 minus MOM3 | 0.0005 | -0.0090 |
| p-value | 0.9132 | 0.0511 |

p-value - Out-of-Sample Alpha
(MOM1 minus MOM3) vs. (UI minus DI): 0.0005

**Panel C- Alphas for Industry Recommendations Net of Momentum Portfolios**

| Industry Recommendation Portfolio (One Month) | In-Sample Alpha | Out-of-Sample Alpha |
|---|---|---|
| UI | 0.0054 | 0.0098 |
| *p-value* | 0.0159 | 0.0004 |
| NI | 0.0041 | 0.0014 |
| *p-value* | 0.0195 | 0.4054 |
| DI | -0.0079 | -0.0053 |
| *p-value* | 0.0530 | 0.2036 |
| UI minus DI | 0.0122 | 0.0145 |
| p-value | 0.0071 | 0.0031 |

## Table 9 (*continued*)

### Panel D – Cross-Sectional Analysis of Industry Recommendation Portfolios

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Port | -0.0045** | -0.0069*** | | |
| | (0.0023) | (0.0023) | | |
| Ind_Rec | | | -0.0058* | -0.0068** |
| | | | (0.0031) | (0.0033) |
| Log(Firm Size) | | -0.0018 | | -0.0011 |
| | | (0.0016) | | (0.0017) |
| Log(1+MB) | | 0.0053 | | 0.0068 |
| | | (0.0085) | | (0.0081) |
| Market_Beta | | 0.0028 | | 0.0028 |
| | | (0.0048) | | (0.0048) |
| Past_Ind_Ret | | 0.0083 | | 0.0124 |
| | | (0.025) | | (0.0242) |
| Constant | 0.0177*** | 0.0251 | 0.0202*** | 0.0177 |
| | (0.0056) | (0.0175) | (0.0066) | (0.0185) |
| Observations | 1,548 | 1,548 | 1,548 | 1,548 |
| R-squared | 0.066 | 0.505 | 0.083 | 0.512 |
| Number of groups | 87 | 87 | 87 | 87 |