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Are analysts biased? An analysis of stock recommendations that perform contrary to expectations

Abstract

This paper seeks to test whether analysts are prone to behavioral biases when making stock recommendations. In particular, we work with stocks whose performance subsequent to a new buy or sell recommendation is in the opposite direction to the recommendation. We find that these "nonconforming" recommendations are associated with overconfidence bias (as measured by optimism in the language analysts use), representativeness bias (as measured by previous stock price performance, market capitalization, and book-to-market), and potential conflicts of interest (as measured by investment banking relationships).

Our results demonstrate that potential conflicts of interest significantly predict analyst nonconforming stock recommendations. This supports recent policy-makers' and investors' allegations that analysts' recommendations are driven by the incentives they derive from investment banking deals. These allegations have led to implementation of rules governing analyst and brokerage house behavior. However, our finding that psychological biases also play a major role in the type of recommendation issued suggests that these rules may work only in as far as regulating conflicts of interest, but will have a limited role in regulating the cognitive biases to which analysts appear to be prone. Our results suggest that, as a result of this, analyst stock recommendations are likely to continue to lack investment value.

Keywords: analysts' recommendations, analysts' incentives, behavioral finance, overconfidence, representativeness bias

JEL classification: G12, G14

1. Introduction

Sell-side analysts play an important role in the pricing of stocks in financial markets. Grossman and Stiglitz (1980) show that stock prices cannot perfectly reflect all information that is available, and therefore analysts devote enormous resources to gathering new information. Analysts deserve to be compensated as information gatherers. Beaver (2002) indicates that efficient analyst information processing facilitates efficient security price setting, while Fernandez (2001) shows that analysts produce information that is the “life-blood” of both the market and the individual investor.

Although research attests to the importance of financial analysts for the efficient functioning of the capital markets, in the recent past strong doubts have been expressed about the credibility and objectivity of their stock recommendations. Specific concerns related to the fact that analysts’ recommendations were overly optimistic and did not seem to reflect their true beliefs about the stocks they were reporting on. By mid-2000, the percentage of buy recommendations had reached 74% of total recommendations outstanding while the percentage of sells had fallen to 2% (Barber et al., 2006). The main reason held to be responsible for this unequal distribution of buy and sell recommendations was that optimistic analyst recommendations could earn their investment bank employers large fees from corporate finance transactions.

The problem of optimistic research reports and the public outcry over analysts’ conflicts of interest led to intervention by policy-makers and professional bodies who responded by implementing regulations to govern brokerage firms and analysts. In September, 2000, the Securities and Exchange Commission (SEC) implemented Regulation Fair Disclosure (Reg FD). Reg FD was meant to curb the practice of asymmetric information provision where top executives in companies would disclose information to particular analysts, often to those working for the investment banks with whom they had ongoing business relationships. In July, 2002, the National Association of Securities Dealers (NASD) and the SEC issued NASD 2711 and Rule 472 respectively. Overall, these two regulations require analyst research reports to display the proportion of the issuing firm’s recommendations that are buys, holds and sells. In April 2003, the “Global Analyst Research Settlement” was reached between the top ten

US brokerage firms and the SEC, New York Stock Exchange (NYSE), NASD and the New York Attorney General. This led, inter alia, to these brokerage firms paying $1.4bn in penalties for alleged misconduct resulting in investors losing large sums of money from trading on their analysts' stock recommendations during the technology bubble. Importantly, however, the intervention of policy-makers and regulators assumes that the problem of optimistic analyst reports is caused only by their conflicts of interest.

Research also finds that although analysts issue optimistic reports on most of the stocks they cover, their recommendations lack market impact. For example, Barber et al. (2001) and Mikhail et al. (2004) show that, after accounting for risk and transaction costs, investors do not earn better than average returns from following analysts' stock recommendations. Womack (1996), on the other hand, finds that new buy stock recommendations continue to go up for four to six weeks after the new stock recommendation is made, while new sell recommendations lead to stock prices drifting significantly lower for six more months. His results suggest that the average level of recommendation has little investment value but changes in level are valuable, although for a limited time. These research findings lead to the question of what causes analysts to issue stock recommendations that lack investment value.

This paper argues that an important determinant of the apparent judgmental errors made by analysts is cognitive bias. Although there are various cognitive biases documented in the behavioral finance literature, two salient biases recognized as key in explaining the "irrational" behavior of market participants are overconfidence and representativeness.

Overconfidence is defined as overestimating what one can do compared to what objective circumstances would warrant. The more difficult the decision task, and the more complex it is, the more successful we expect ourselves to be. Overconfidence may help to explain why investment analysts believe they have superior investment insights, and yet their stock recommendations are of limited investment value. Various authors suggest the overconfidence of investors, including analysts, plays a major role in the anomalies observed in financial markets. For example, Odean (1998a) looks at the buying and selling activities of individual investors at a discount brokerage. On average the stocks that individuals buy subsequently underperform those they sell even when liquidity demands, risk management, and tax consequences are taken into consideration.

He suggests that this behavior of selling winners too soon is motivated by overconfidence. Barber and Odean (2001) assert that rational investors trade only if the expected gains exceed transaction costs. But overconfident investors overestimate the precision of their information and thereby the expected gain of trading.

The representativeness heuristic (Tversky and Kahneman, 1974) involves making judgments based on stereotypes rather than on the underlying characteristics of the decision task. People tend to categorize events as typical or representative of a well-known class and then, in making probability estimates that overstress the importance of such a categorization, disregard evidence about the underlying probabilities. One consequence of this heuristic is for people to see patterns in data that is truly random and draw conclusions based on very little information. Shefrin and Statman (1995) indicate that investors believe that good stocks are stocks of good companies, which is not necessarily true. This is rooted in the representative bias, which supports the idea that winners will always be winners and losers will always be losers. DeBondt and Thaler (1985) argue that because investors rely on the representative heuristic they could become overly optimistic about past winners and overly pessimistic about past losers. This bias could cause prices to deviate from their fundamental level.

The aim of this paper is to establish whether policy-makers are addressing the only important issue in seeking to address conflicts of interest alone, or whether other factors, in particular, analyst cognitive bias, which may be difficult to regulate, also play a major role in influencing analysts to issue stock recommendations that lack market impact.

Using an appropriate benchmark metric, we first evaluate the performance of analyst stock recommendations over the 12-month period after their recommendations are changed from their previous categories to new buy (sell) categories. In line with the results of earlier studies (e.g. Womack, 1996), we find that the stockmarket reacts significantly to new buy recommendations only in the recommendation month (month 0), with no subsequent drift. Conversely, the market reacts significantly and negatively to new sell ratings, not just in the month of recommendation change. It also exhibits a significant post-recommendation stock price drift of -8% in the subsequent 12 months over and above the 5.6% fall in the recommendation month.

With both buy and sell recommendations, many stocks perform different to expectations. For instance, there are new buys (sells) that underperform (outperform) the benchmark 12 months after the recommendation is made. To focus on these stocks where analysts can be viewed, *ex post*, as having made erroneous judgment calls, we therefore work with cases where subsequent stock performance is contrary to expectations. We find in our data that 56% of new buy recommendations underperform the appropriate benchmark 12 months after the recommendations are changed and, of these, more that 6 out of 10 stocks (62%) underperform the benchmark by at least 20% by month 12. On the other hand, 70% of new sell recommendations perform as expected over the 12-month period and only 16% outperform the benchmark by at least 20% by month 12.

We then establish which factors are associated with these "contrarian" stocks. We find that analysts' stock recommendations that perform contrary to expectations are associated with (i) overconfidence bias (as measured by the optimistic tone of language used in their research reports), (ii) representativeness bias (as measured by previous positive stock price performance, size of firm, and growth status of the firm (book-to-market)), and (iii) corporate relationships between their investment bank employers and the firms they are following. These findings imply that the regulations recently promulgated to govern analyst and brokerage house activity, however successful they might be in dealing with analyst conflict of interest, may have only limited impact on problems associated with analyst cognitive bias, which is probably inherent in the nature of their work.

The remainder of the paper is organized as follows: the next section formulates our research hypotheses. In section 3 we present our data and in section 4 we describe our research method. Section 5 discusses the price performance of new stock recommendations both for our full sample and also for our nonconforming stocks. Section 6 presents our empirical results, and concluding section 7 discusses these and their implications.

2. Hypotheses

Our null hypotheses about the determinants of nonconforming analysts' stock recommendations are grouped under two broad categories, cognitive biases and corporate relationships.

2.1. Cognitive biases

Tversky and Kahneman (1974) postulate that when people are faced with complicated judgments or decisions, they simplify the task by relying on heuristics or general rules of thumb. Because of the complex nature of the analyst's work, we postulate they are likely to be prone to cognitive biases, in particular, overconfidence and representativeness.

2.1.1. Overconfidence bias

We measure overconfidence bias by the tone of language that analysts use in their research reports. To do this we employ *Diction* (Hart, 2000), a computerized content analysis package.[1] *Diction* detects semantic tonalities in a document and employs a series of lexicons for the occurrence of words that represent various pre-specified semantic tones in sample comparison databases.[2] (Further discussion on the Diction package is given in section 4.3 below). To measure overconfidence we use the variables OPTIMISM and CERTAINTY, provided by *Diction*. OPTIMISM is defined in *Diction* as language endorsing some person, group, concept or event or highlighting their positive entailment, while CERTAINTY is defined as language indicating resoluteness, inflexibility, completeness and a tendency to speak *ex cathedra*. Our first null hypothesis is thus defined as follows:

> ***$H1_0$: The tone of the language used by investment analysts in their research reports to justify their stock ratings is not optimistic independent of whether the stock recommendation is new buy or new sell.***

[1] Broadly speaking content analysis methodology documents the frequency with which ideas/ concepts appear in a text. An underlying assumption of content analysis is that frequency of occurrence is a proxy for the importance of that factor in driving the course of an argument in a document.

[2] These dictionaries were constructed by expert linguists from the analysis of more than 20000 texts. Its automated nature both for coding and quantification makes it attractive as a research instrument (Sydserff and Weetman, 2002).

If overconfidence bias (as measured by OPTIMISM and CERTAINTY) influences analyst stock recommendations, then we expect it to have a significant positive (negative) impact on their new buy (sell) ratings that subsequently perform in a contrarian manner.

2.1.2. Representativeness bias

2.1.2.1. Activity

We use the *Diction* variable ACTIVITY to measure the degree of representativeness bias in the language used by analysts when preparing their research reports. ACTIVITY is defined in *Diction* as language featuring movement, change, and the implementation of ideas and the avoidance of inertia. Fogarty and Rogers (2005) conclude that analysts' decisions about firms' stock tend to be influenced by their knowledge of corporate plans, merger/acquisition talk, or any suggestion of proffered change in corporate direction. Our second null hypothesis is therefore stated as follows:

> ***$H2_0$: The tone of the language used by investment analysts in their research reports to justify their stock ratings is not positively biased towards the level of activity (or change) taking place within the firm.***

2.1.2.2. Previous price performance

Stickel (2000) posits that Wall Street "darlings" are stocks with, among other characteristics, recent positive EPS momentum and surprise, and recent positive relative price momentum. Analysts have incentives to give buy recommendations to stocks with these financial characteristics because they follow from documented momentum pricing anomalies, and because they are actionable ideas that generate trading commissions. We take previous price momentum as another measure of representativeness bias in that analysts might assume that the previous price performance of the stock is representative of the future performance of the stock. Null hypothesis 3 is therefore established as follows:

> ***$H3_0$: Price momentum either has a negative (positive) or insignificant impact on whether analysts will issue a buy (sell) recommendation which does not perform as expected.***

Variable PRICE_MOM is used to capture the effect of price momentum on analysts' new buy/sell recommendations. We define PRICE_MOM as the percentage price change in a stock in the year prior to the recommendation change expressed on an average monthly basis. If a stock's past performance has a direct influence on the type of stock recommendation that an analyst issues, positive PRICE_MOM will be associated with buy recommendations and negative PRICE_MOM with sell recommendations. That is, firms that receive buy recommendations are those that have consistently performed well in the recent past, while sell recommendations are given to stocks that have performed poorly over the previous period.

2.1.2.3. Size of firm

We consider firm size as another potential aspect of representativeness bias in that analysts might assume that a large (small) firm is a good i.e., well-managed (bad) firm, and thus will subsequently outperform (underperform) the benchmark (Solt and Statman, 1989). Null hypothesis 4 is therefore established as follows:

$H4_0$: Firm market capitalization does not have any significant impact on the type of stock recommendation issued by analysts for stocks which subsequently perform contrary to expectation.

Variable FIRM_SIZE is used to pick up the effect of market capitalization on the determination of buy and sell recommendations. As in Mikhail et al. (2004), size of the firm is measured using the natural logarithm of the market value of equity for the firm at the end of the financial year preceding the recommendation revision. Our conjecture is that large firms are less likely to receive sell recommendations than small firms; on this basis, new nonconforming buy recommendations are likely to be associated with larger values of FIRM_SIZE, and new non-confirming sell recommendations with smaller values on this variable.

2.1.2.4. Book-to-market

Most buy recommendations are made by analysts who tend to favor "growth" over "value" stocks. This is because growth stocks exhibit greater past sales growth and are expected to grow their earnings faster in the future. Financial characteristics of preferred stocks include higher valuation multiples, more positive accounting accruals, investing a greater proportion of total assets in capital expenditure, recent positive relative price momentum, and recent positive EPS forecast revisions (Jegadeesh et al., 2004). Based on these arguments, we expect that stocks with low book-to-market ratios (growth stocks) are more likely to receive buy recommendations than stocks with high book-to-market ratios (value stocks). Book-to-market can be used to measure representativeness bias on the basis that current growth characteristics could be taken as representative of the stock's likely future performance by analysts. Null hypothesis 5 is therefore established as follows:

$H5_0$: The firm's book-to-market ratio does not have any significant impact on the type of recommendation issued by analysts for stocks which subsequently perform contrary to expectation.

Variable BTOM is used to capture the effect of book-to-market on our nonconforming stock recommendations. It is measured as book value per share divided by market price of equity. Book value per share is calculated as total assets minus total liabilities deflated by the number of shares outstanding at the end of the firm's previous fiscal year. Market value of equity is calculated by dividing the firm's market value by the total number of shares in issue (Mikhail et al., 2004). All accounting measures are obtained from *COMPUSTAT*. High values of BTOM are expected to be associated with buy recommendations and low values with sell recommendations.

2.2. Conflicts of interest: corporate relationships between investment banks and firms

Analyst compensation methods associated with potential or actual corporate finance relationships between their investment bank employers and the firms they report on have been a serious cause for concern in the recent past. Null hypothesis 6 is therefore formulated as follows:

$H6_0$: There is no relationship between the analyst's new stock recommendation for a subsequently nonconforming stock and whether there is an existing relationship between the investment bank and the particular firm.

Variable INVEST_RELATE is constructed to measure the relationship between the firm being researched and the investment bank which employs the analyst. This variable takes the value of 0 if no relationship exists between the firm and the brokerage house, 1 if the brokerage house is an underwriter[3] of the firm or has current holdings[4] in the firm, and 2 if the brokerage firm is both an underwriter and has a current holding. Information about such relationships between firms and brokerage houses is found in the disclosure section of analysts' research reports. Higher values of INVEST_RELATE are expected to be associated with new buys, and lower values with new sells. That is, firms which have some form of relationship with the analyst's investment bank are more likely to receive buy recommendations, while firms with no such relationship are more likely to receive sell recommendations, *ceteris paribus*.

2.3. Control variables

2.3.1 Analyst following

We introduce analyst following as a control variable to ensure that the test of the relation between recommendation type for nonconforming stocks and our cognitive bias and conflict of interest variables are not confounded by the number of analysts following the firm.

Analyst following is perceived to be essential for the correct valuation of the firm by the market. Bhushan (1989) and Hussain (2000) observe that the number of analysts following a stock is positively related to the number of institutions holding the firm's shares, the percentage of the firm held by institutions, firm return variability, and firm size. For example, large firms are found to have a larger analyst following than small firms. O'Brien and Bhushan (1990) and Hussain (2000) note that analyst following is higher for industries with regulated disclosures and with a higher number

[3] Underwriter means that the investment bank acts as an underwriter by providing advice to the issuing firm, by distributing securities, by sharing the risk of issue and by stabilising the aftermarket.
[4] Current holding means one of the management team owns shares in the company being researched or does some work for the company.

of firms. Lang and Lundhom (1996) document a positive association between analyst following and analyst forecast accuracy.

Our variable ANALY_FOLL is represented by the total number of analysts following the firm taken from the Thomson Financial, *Institutional Brokers' Estimate System* (*IBES).* It is postulated that there might be some indirect relationship between the number of analysts following the firm and the recommendation issued. We know that the larger the firm (in terms of market capitalization) the greater is the analyst following. As we have seen above, size of firm could have an influence on the type of stock recommendation issued. Therefore, we might expect higher values of ANALY_FOLL to be associated with new buy recommendations and lower values with new sell recommendations.

2.3.2. Target price

Target price is introduced as a second control variable. Brav and Lehavy (2003) document a significant market reaction to changes in target prices, both unconditionally and conditional on contemporaneously issued stock recommendations and earnings forecast revisions. Their results suggest that price targets have information content beyond that which is contained in the stock recommendation. As such, stock recommendations should not be looked at in isolation by investors but be used together with target prices. Analysts associate target price direction as being indicative of what the stock recommendation direction should be, which means that target price is considered to be representative of the type of stock recommendation analysts will issue.

Target price change variable TGTPRCE_CHNG is constructed to measure the effect of target prices on the determination of buy and sell recommendations. This control variable is represented by the 12-month percentage change in the analyst's projected target price for a firm; it is computed as the new target price divided by the old target price minus 1. Current and previous target prices are obtained from the respective analyst research reports. In cases where the previous target prices are not available in the current reports, such data is obtained from the Thomson Financial *First Call* database. It is anticipated that the coefficient on TGTPRCE_CHNG will be positive, with high (low) values on this variable associated with new buy (sell) recommendations.

3. Data and descriptive statistics

The source of analysts' stock recommendations used in this research is the *IBES* detailed recommendation file. Our sample covers stock recommendations for the period from January 1, 1997 through to December 31, 2003 issued by the top-ten US brokerage firms as identified in the December 2001 issue of the *Institutional Investor* survey of institutional investors (Womack, 1996).

Different brokerage firms use different stock rating systems which *IBES* recodes into five categories "strong buy", "buy", "hold", "underperform" and "sell". In line with earlier research (e.g. Womack, 1996), these are further reclassified in this research into three categories "buy", "hold", and "sell" to allow for easy and intuitive interpretations of our empirical results. This reclassification is also consistent with rule NASD 2711 which requires brokers to partition their recommendations into just these three categories for disclosure purposes, regardless of the actual rating system they use.

Only changes in recommendations and not reiterations are employed in this study because changes in recommendations have higher information content than reiterations (e.g., Womack, 1996; Francis and Soffer, 1997). Changes examined are new buy recommendations following previous sells or holds, and new sell recommendations from previous buys and holds.

Table 1 shows how we arrive at our final sample. The January 2004 *IBES* database contains a total of 363,000 stock recommendations. Eliminating those recommendations made outside our sample period of January 1, 1997 to December 31, 2003, recommendations not issued by top-ten brokerage firms, reiterations and utilities and financial firms leaves a total of 16,198 recommendation changes. Each such stock must have its market price information available in the *Centre for Research in Security Prices (CRSP)* database when the change in recommendation is made, lack of such data leads to the elimination of around a further 2,000 cases. The final sample consists of 14,169 changes in recommendation.

Table 1 here

Figure 1 presents the distribution of new buys, holds and sells over our sample period. Consistent with Barber et al. (2006), it shows the dramatic change in the distribution of stock recommendations over the 7 years; this is particularly conspicuous in 2002 when there are 23% buys, 51% holds and 26% sells. During 2000 the ratio of new buys to sells reaches its highest level of 49:1 but plunges to 0.9:1 in 2002. While this decline may be attributed to other factors such as economic conditions and the collapse in market prices, it is most likely due to the implementation of NASD 2711 and Rule 472 (Barber et al., 2006; Madureira, 2004) which were put into effect on July 9, 2002.[5]

Figure 1 here

Table 2 provides the matrix of recommendation changes for the whole sample period. Thirty-five per cent of the changed recommendations are new buys, 52% are new holds, while 13% are new sells. A very large proportion of new buy (sell) recommendations are previously from the hold category. Analysts are more likely to downgrade stocks than upgrade them (59% versus 41%). About 77% of downgrades are from buy to hold, 19% are from hold to sell, while only 4% are from buy to sell. On the other hand, 82% of upgrades are from hold to buy, 15% are from sell to hold, while 3% are from sell to buy. This pattern indicates that movement in stock recommendations is very rarely from one extreme category to another, i.e., directly from buy to sell and vice versa; movement in recommendations is almost always through the intermediate hold category.

Table 2 here

[5] Refer to Barber et al. (2003) for more information about these rules.

4. Method

This section describes how we measure the market impact of new stock recommendations and target prices, how we select our nonconforming stocks, and how we conduct our content analysis of analyst research reports. The final sub-section describes our logistic regression approach to determining the extent to which analyst cognitive bias and conflicts of interest might be driving their recommendations for stocks which subsequently perform contrary to expectations.

4.1 Method used to evaluate stock recommendations

The event study method is used to examine the reaction of investors to changes in financial analysts' stock recommendations. This approach is based on the assumption that capital markets are sufficiently efficient to evaluate the impact of new information (events) on firm value. The relevant event date in this study is defined as that date when the stock recommendation is changed from its previous rating to new buy or sell ratings.

4.1.1. Return generating methodology

The reference portfolio method with the event firm matched on the basis of industry, size and book-to-market is used as our benchmark approach. Intuitively, matching primarily by industry is appropriate compared with an economy-wide benchmark, because analysts often study firms within their industry context and specialize in particular industries. Many analysts even provide a full industry analysis before they conduct specific stock analysis in their research reports. And, to a great extent, the final decisions they make on the individual stocks they follow are influenced by what is happening to the respective industry at large. For example, Boni and Womack (2006) find that analysts take strong cues from recent industry returns in revising the ratings of the stocks they follow. In fact, most of the brokerage firms in this study define their stock recommendation categories in terms of expected future stock performance relative to respective industry average performance.

Concurrent controls for size and book-to-market are expected to capture the cross-sectional variation in average monthly returns. These measures are good proxies for common risk factors (Fama and French, 1992; 1993) inherent in different industries. Although previous studies (e.g., Carhart, 1997) have established that momentum is also an important factor in explaining stocks' abnormal returns, it is not controlled for in our expected return generating model as the resulting reference portfolios would contain too few cases.

4.1.2. Constructing benchmark portfolio returns

To form industry reference portfolios, stock industry codes are obtained from the *CRSP* database. These codes are then used to classify all stocks from NYSE, AMEX and NASDAQ with data in the *CRSP* stock-return file into industry deciles in the manner of Fama and French in their 12-industry portfolios classification process,[6] although, in our case, only 10 industry portfolios are used because the finance and utility industries are excluded. Within each industry decile, firms are ranked into thirds based on size, and then broken down further into three groups based on their book-to-market ratio. Thus, a total of 90 reference portfolios grouped by industry, size, and book-to-market are formed. For example, the stocks in portfolio 1 are stocks in industry 1, are in the largest size group, and within the highest third of book-to-market ratios.[7] Portfolios are formed in June of each year, starting in June 1997, and monthly returns are calculated for the portfolios for the following 12 months after the portfolio formation date. For each benchmark portfolio, its equally-weighted portfolio return is calculated as the arithmetic return of all securities in the particular industry, size and book-to-market intersection set in the year of portfolio formation.

Size is measured by market capitalization calculated as month-end closing price multiplied by the number of shares outstanding. Size data is obtained from *CRSP*. Book value is defined as *COMPUSTAT* book value of stockholders' equity (*COMPUSTAT* item 60). A six-month lag is used in the case of book value to allow for delay in the publication of annual financial statements (Barber and Lyon, 1997). Thus, for

[6] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.
[7] For robustness, we also reverse the criteria and sort by industry, book-to-market, and size in that order. All our results remain the same.

calculating the book-to-market ratio for year t, the book-value used would be from the financial statements for year t-1.

For each sample firm i, the buy-and-hold abnormal return ($BHAR_{iT}$), where T is the holding period in months, is calculated as the difference between the firms buy-and-hold return (R_{it}), and the buy-and-hold return on the respective reference portfolio p (R_{pt}) over the period commencing at the begining of the month following the recommendation, and ending T months later. Firm BHARs are calculated as follows:

$$BHAR_{iT} = \prod_{t=1}^{T}(1 + R_{it}) - \prod_{t=1}^{T}(1 + E(R_{pt})) \quad (1)$$

Some stocks are delisted between the date of change in stock recommendation or target price, and before the end of the 12-month period. For all stocks that have missing returns after the dates of their new stock recommendations, the returns on the corresponding reference portfolios are deemed to be their realized returns (Barber and Lyon, 1997).[8]

4.2 Method for selecting nonconforming stocks

In the preceding section, we discuss how we measure stock performance over a 12-month period. This section describes how we select stocks that have not performed as expected by the analyst, i.e., new buy (sell) recommendations that underperform (outperform) the reference portfolio benchmark over the 12-month period following the changed stock recommendations.

In theory, a ‘buy’ recommendation is issued when a stock is perceived to be undervalued. Conversely, a ‘sell’ recommendation is issued when a stock is believed to be overvalued, while a stock awarded ‘hold’ is believed to be fairly priced. The definitions of stock recommendations by the top ten brokerage firms follow this same

[8] In order to avoid possible issues of cross-sectional dependence arising from possible multiple recommendations issued in respect of the same stock we adopt the approach used in Stickel (1995) whereby all recommendations and target prices of the same type that are changed within a period of 6 months of the first change (either made by the same broker or a different broker) are dropped from our analysis.

idea but go even further in specifying the actual percentages by which the stocks that are classified to each of the three categories are expected to outperform/underperform the respective industry averages. Generally, according to brokerage firms, a buy (sell) recommendation is expected to outperform (underperform) the industry benchmark by 10% or more, depending on risk.

The selection of nonconforming stock recommendations is thus based on how the stock ratings are defined by our sample brokerage firms. Therefore, in this research, a buy recommendation is deemed to be performing contrary to analysts' expectations if the associated subsequent stock performance over the following 12-month period is at least 10% lower than that of the respective benchmark. Conversely, a sell recommendation is not conforming to analysts' expectations if subsequent performance exceeds that of the benchmark by at least 10% over the next 12 months.

However, in our formal analysis, we increase the cut-off percentage to at least 20% so that only extreme cases of non-conformance are analyzed, i.e., only buys (sells) that underperform (outperform) the reference benchmark by at least -20% (+20%) are considered. This approach provides a much cleaner test because if the analyst recommendation is associated with stock returns in line with the analyst's output, then it is difficult to distinguish between bias and valid judgment. Investigating extreme cases of stocks with nonconforming subsequent stock returns is an attempt to remove analysts' correct judgmental processes. Although analysts may be biased, even if the stock's performance is in line with what is expected, we believe potential bias may be much more directly observable when the outturn is demonstrably wrong to a significant extent, i.e., at least 20% below or above what is expected. Therefore, focusing on extreme nonconforming situations is viewed as being a cleaner way of testing our research hypotheses than using, for example, a random sample of all new buy and new sell cases.

4.3 Content analysis method

Data for $H1_0$ and $H2_0$ is collected using the automated computerized content analysis package *Diction* (Hart, 2000). This measures a text for its verbal tone across five variables namely: *optimism, certainty, activity, realism and commonality*. The use of *Diction* is well-established in the applied linguistics literature (e.g., Hart, 2000; 2001). Its validity and reliability as a computerized content analysis program has been widely attested to (e.g., Morris 1994; Sydserff and Weetman, 2002). *Diction* has been mostly used in accounting applications but less so in finance. Most similar to this research, Fogarty and Rogers (2005) use *Diction* in conjunction with other content analysis software to study financial analyst reports and argue that we can understand analysts and their work better if we do not just analyze the numerical values in their reports, but also the textual data. They conclude that analyst reports are characterized by bias, skew and lack of science. This study builds on Fogarty and Rogers (2005) by also applying *Diction* to analyst reports, but with the specific intention of measuring analysts' potential behavioral biases.

4.4 Factors which differentiate between nonconforming new buy and new sell recommendations

We fit a logistic regression model using maximum likelihood estimation to determine the factors that differentiate between the nonconforming new buy and new sell recommendations. In this model, the dependent variable is RATING, and the independent variables, defined in section 2 above, are OPTIMISM, CERTAINTY, ACTIVITY, PRICE_MOM, FIRM_SIZE, BTOM, INVEST_RELATE, while ANALY_FOLL and TGTPRCE_CHNG are control variables. Binary variable RATING denotes the nonconforming buy or sell stock recommendation. RATING = 1 if an analyst issues a new buy recommendation which underperforms its respective reference portfolio benchmark by at least -20%, and 0 if a new sell is issued that outperforms the respective reference portfolio benchmark by at least +20%.

Diction variables OPTIMISM, CERTAINTY and ACTIVITY, which serve as proxies for overconfidence and representativeness psychological biases, are derived from the actual research reports written by analysts to justify their stock recommendations. TGTPRCE_CHNG, the variable which measures the percentage change in analyst projected target price, and INVEST_RELATE, the variable measuring the relationship between brokerage houses and firms, are also obtained from the same research reports that provide scores for OPTIMISM, CERTAINTY and ACTIVITY. If TGTPRCE_CHNG information is missing from the research reports, such information is obtained from the *First Call* database. PRICE_MOM, FIRM_SIZE and BTOM values are calculated from data obtained from the *CRSP* database and *COMPUSTAT,* while ANALY_FOLL is taken from *IBES*.

Our logistic model is specified in equation 2 as follows:

$$\text{RATING} = \text{LOGIT}(\pi) = \text{LN}\left(\frac{\pi}{1-\pi}\right)$$

$$= \alpha + \beta_1\text{OPTIMISM}_{j,t} + \beta_2\text{CERTAINTY}_{j,t} + \beta_3\text{ACTIVITY}_{j,t}$$
$$+\beta_4\text{PRICE\_MOM}_{j,t-1} + \beta_5\text{FIRM\_SIZE}_{j,t-1} + \beta_6\text{BTOM}_{j,t-1}$$
$$+\beta_7\text{INVEST\_RELATE}_{j,t} + \beta_8\text{ANALY\_FOLL}_{j,t}$$
$$+\beta_9\text{TGTPRCE\_CHNG}_{j,t-1} + \varepsilon_{j,t} \qquad (2)$$

where RATING = 1 for nonconforming new buy stocks and 0 for nonconforming new sell stocks, $\beta_1 \ldots \beta_9$ are the logistic regression parameter estimates, and $\varepsilon_{j,t}$ is the error term.

5. Market reaction to changes in stock recommendation

This section first reports the medium-term market reaction to all stock recommendations that are changed to buy and sell categories. It then provides parallel results for the stocks that do not perform as expected 12 months after the change in recommendations.

5.1 Performance of new buy and new sell recommendations

Table 3 summarizes the abnormal return performance attributable to new buy and new sell recommendations. Panel A shows that the BHARs for our 2,230 new buy recommendations are driven mainly by the returns in the month of recommendation change (t=0), and there is no post-recommendation drift. Thus, mean abnormal return in the month of new recommendation is +5.7% (t = 13.6) and does not change significantly in the subsequent months. By month 12, the mean BHAR is 7.9%, while the median is -5.0%. A total of 123 firms (5.5%) are delisted over the 12-month performance evaluation period. The fact that we find that the market reaction to new buys is only significant in month 0 corroborates the findings of Stickel (1995), Womack (1996) and Barber et al. (2001) that the value of new buy recommendations is short-lived and lasts only for one month.

Table 3 here

Table 3, panel B, however, provides clear evidence of continuing negative market reaction for up to 12 months following new sell stock recommendations. Mean abnormal return in the recommendation month for our 1,070 cases is -5.6% (t = 6.8), and increases to -13.6% (t = -4.7) by month 12. Median BHAR is significantly negative over the 12-month period, rising from -4.3% in month 0 to -19.9% by month 12. A total of 79 firms (7.4%) are delisted over the period of performance evaluation. Figure 2 graphs the intertemporal BHAR patterns for both new buys and sells, visually highlighting the differences in return behavior over time.

Figure 2 here

The performance of new sell recommendations observed here is again consistent with the findings of Stickel (1995), Womack (1996) and Barber et al. (2001) in that reaction to negative stock recommendations is incomplete in the recommendation month, with the market continuing to underreact for many months subsequently. Although earlier studies observe underreaction over a 6-month period, here we find such underreaction continues for at least 12 months. This post-recommendation drift in BHARs for new sell recommendations lends support to the idea that investors find difficulty in adjusting their expectations about future stock performance, at least in the bad news case. Such slow assimilation of news by investors, behavioral research proposes, can explain the market underreaction phenomenon more generally (e.g., Barberis et al., 1998).

5.2. Performance of nonconforming stocks

Table 4, panel A shows that 3 in 5 (62%) of all new buy recommendations earn positive returns in the month that the recommendation is changed. However, by month 12 after the stocks are first awarded a buy recommendation, less than half (45%) still have positive BHARs with the majority (55%) experiencing negative returns. The interesting question is what percentage of these stocks actually attains at least the minimum 10% outperformance of the benchmark stipulated by the brokerage firms in their definition of buy recommendations.

Table 4 here

Panel A also shows that, on average, only just over a third (35%) of stocks that receive new buy status outperform the benchmark by at least 10% over the 12-month period, the minimum outperformance required by our brokerage firms to represent a buy recommendation; whilst two-thirds (65%) do not. In fact, of the new buy cases that underperform the benchmark, no less than 6 out of 10 stocks (62%) underperform the benchmark by -20% or more by month 12.[9] These are the stocks that are of most interest in this research, which has as its main purpose to establish why such stocks are awarded a new buy recommendation and yet perform so poorly and contrary to expectation.

In the case of new sell recommendations, table 4, panel B indicates that in the month of the recommendation change 3 in 5 of the stocks in our sample receiving sell ratings (63%) earn negative abnormal returns, while over a third (37%) earn positive returns. However, in contrast to Panel A, by month 12 following the recommendation change, no less than 70% of these stocks are earning negative returns. Six out of 10 (59%) of these stocks with a sell rating underperform the benchmark by at least 10%, which is the minimum percentage underperformance required by the brokerage firms to define a sell recommendation. Only 16% of these stocks outperform the benchmark by an extreme +20%.

In summary, table 4 demonstrates how new sell recommendations are performing far more closely with analyst expectations than their new buy counterparts 12 months after the recommendation change. This is further substantiated by the fact

[9] Or 34% of all new buys- see last column.

that the percentage of sell stocks outperforming the appropriate benchmark by an extreme 20% is only half (16%) the equivalent percentage of extreme underperformance cases with new buys (34%).

6. Results

In this section, we first present the characteristics of our nonconforming new buy and new sell recommendations and then report our empirical results, which seek to explain the analyst ratings for these stocks in terms of cognitive bias and conflicts of interest. Of the 1,220 new buy stocks that underperform their respective benchmark by month 12, 34% (759) underperform by at least -20%. However, only a third (261) of these stocks have an accompanying research report available. On the other hand, 207 (30%) new sell stocks outperform their respective benchmark 12 months after the recommendations were downgraded to a sell rating. Of those, about 111 (16%) outperform the benchmark by at least +20%. Research reports are available for just under two thirds of these new sell recommendations (71) and are spread throughout the sample period. All available research reports are obtained from the Thomson Financial *Investext Plus* database.

6.1. Descriptive statistics

Table 5 provides statistics for the main variables used in this analysis. Panel A refers to our 261 underperforming new buy recommendations, and panel B to our 71 outperforming new sell recommendations. Results show that firms that are awarded new buy recommendations have larger market capitalization (mean FIRM_SIZE =$11.8 billion) compared to their new sell counterparts (mean FIRM_SIZE =$3.2 billion) with the difference in means significant at the 0.01% level. The new buy stocks have generally performed well in the recent past with prior 12-month mean monthly return (PRICE_MOM) of 1.8% compared with new sells, when mean PRICE_MOM = -1.5%; the mean difference between the two monthly returns of 3.3% is significant at the 0.01% level. New buy stocks have low book-to-market ratios (mean BTOM = 0.38) and, as such, may be classified as glamour stocks, whereas new sells stocks have high book-to-market ratios (mean BTOM = 1.00) and may be classified as value stocks, with difference in means significant again at 0.01%. The mean number of analysts following new buy stocks (mean ANALY_FOLL = 39) is higher than the number following new sell stocks (mean ANALY_FOLL = 24). This difference in numbers of analysts making nonconforming buy recommendations and nonconforming new sell recommendations is significant at 0.01% level. Finally, not surprisingly, the target price one year out is predicted to rise significantly (mean TGTPRCE_CHNG = 16%) in the case of new buys and to fall significantly in the case of new sells (mean TGTPRCE_CHNG = -14%), with difference in means again significant at 0.01%.

As expected the language used by investment analysts to justify their research reports is more optimistic for new buys than is the case for new sells (significant at the 10% level). However, there is no difference in the language indicating CERTAINTY and ACTIVITY between the nonconforming new buy and new sell analyst reports. The average number of corporate relationships (INVEST_RELATE) is higher for new buys than it is for new sells (0.95 compared to 0.73), with difference significant at the 5% level.

Table 5 here

Kurtosis for variables ACTIVITY, FIRM_SIZE and TGTPRCE_CHNG for nonconforming new buy recommendations indicates severe peaking compared to their nonconforming new sell recommendation equivalents. These same variables are also highly positively skewed (except ACTIVITY which is negatively skewed) compared with their nonconforming new sell counterparts.

6.2 Correlation matrix between variables

Table 6 presents the Pearsonian product moment correlation matrix for the model variables. Correlations between OPTIMISM and CERTAINTY as well as between OPTIMISM and FIRM_SIZE are positive and highly significant. PRICE_MOM has a negative and highly significant relationship with BTOM and a positive and significant relationship with TGTPRCE_CHNG. FIRM_SIZE has a negative and significant relationship with BTOM and a positive and significant relationship with ANALY_FOLL. BTOM has a negative and significant relationship with ANALY_FOLL and TGTPRCE_CHNG, while the correlation between ANALY_FOLL and TGTPRCE_CHNG is also positive and significant.

Table 6 here

6.3 Logistic regression model results

Table 7 reports the results from running the logistic regression model of equation 2. OPTIMISM is positive and significant ($p<0.10$, $\chi^2 = 2.75$) in explaining the type of stock rating analysts issue. This finding is inconsistent with null hypothesis $H1_0$ that the tone of language used by analysts in the research reports they prepare to justify their stock ratings is not driven by optimism. The significance of OPTIMISM suggests that analysts' overconfidence makes them issue stock ratings which eventually perform contrary to expectations. The odds ratio of 1.3 indicates that the odds will increase (greater chance of buy recommendations which significantly underperform the respective benchmark) by a factor of 1.3 for every unit increase in OPTIMISM if all other variables are held constant. However, neither the CERTAINTY nor ACTIVITY variables have any explanatory power. In the former case we cannot reject $H1_o$ with respect to the CERTAINTY measure, and in the latter case, we have no evidence to reject null hypothesis $H2_o$ that the language used by analysts in their reports is not biased with respect to the level of activity or change taking place within the firm.

The parameter estimate for price momentum (PRICE_MOM) is positive and significant at $p<0.001$. This indicates that the probability that analysts will issue a buy recommendation that underperforms the benchmark is higher for stocks that have performed relatively well in the past. This suggests analysts prefer stocks that exhibit good previous performance (Stickel, 2000; Jegadeesh et al., 2004). This finding is inconsistent with null hypothesis $H3_0$ that the impact of price momentum is negative or insignificant in predicting the type of stock recommendation that analysts issue. That analysts appear to use a stock's past performance as being suggestive of its likely future performance is consistent with the operation of representative bias.

The parameter estimate for FIRM_SIZE is positive and significant at $p<0.05$, suggesting that the larger the firm the greater the likelihood that analysts will issue a nonconforming buy recommendation on the stock. This is either because analysts associate size of firm with good performance, or because there are other benefits that analysts derive when they issue buy ratings on large market capitalization stocks. The size effect is well documented in the literature in terms of explaining abnormal returns, but in a contrarian manner. Small firms typically outperform large firms, which is the opposite of what analysts appear to believe. The odds ratio shows that an increase in size of firm by one unit increases the probability of the analyst issuing a nonconforming new buy recommendation by a factor of 2. This empirical finding is inconsistent with null hypothesis $H4_0$ that the size of the firm does not have any significant impact on the type of stock recommendation issued by analysts. These results are consistent with the idea that analysts see FIRM_SIZE (wrongly) as representative (representativeness bias) of a stock's future performance.

The parameter estimate for BTOM is negative, as expected, and significant at $p<0.01$. This result suggests that buy recommendations for stocks that subsequently underperform tend to be associated with glamour stocks. The chance of obtaining a nonconforming buy recommendation decreases when book-to-market increases. This finding is inconsistent with null hypothesis $H5_0$ that the firm's book-to-market ratio does not have any significant impact on type of stock recommendation. Also, this result implies that, according to financial analysts, book-to market is representative of the future performance of the stock, although the sign of their relationship is wrong. The evidence clearly suggests value stocks actually outperform glamour stocks.

Table 7 here

INVEST_RELATE measures whether a corporate finance relationship between the analyst's investment bank and firm being reported on exists. In particular, we are interested in whether associated conflicts of interest have any bearing on the type of recommendation that analysts issue. The parameter estimate for INVEST_RELATE is positive, as expected, and significant at $p< 0.01$. These results are consistent with Lin and McNichols (1998), Michaely and Womack (1999), Barber et al. (2004), and Cliff

(2004) in that our analysts tend to issue more favorable recommendations on the stocks of firms with which their employer has a commercial relationship. The odds ratio associated with analysts issuing a nonconforming buy recommendation, if there is a corporate finance relationship between brokerage house and firm, is 2.9. Thus, we conclude, in contrast to null hypothesis $H6_0$, an existing relationship between brokerage house and firm has a significant impact on the type of recommendation that its analysts issue, which is consistent with conflict of interest concerns.

Control variable analyst following, ANALY_FOLL, has no significant predictive ability. However, the parameter estimate for the control variable, change in target price, TGTPRCE_CHNG, is statistically significant at $p<0.001$, which suggests that there is a strong relationship between target price and the type of recommendation that analysts issue on the stock. Thus, when the target price on a stock is increased (decreased) then the probability that analysts will issue a nonconforming buy (sell) recommendation also increases.

Approximate model explanatory power is 19% with likelihood χ^2-ratio = 64.6, significant at $p<0.001$. This suggests that the model variables as a group play a significant role in the type of stock recommendation that analysts issue, particularly in differentiating between buy and sell recommendations that do not perform as expected.

6.4. Additional tests

To explore further the likely impact of cognitive biases on analyst stock recommendation decisions we work with full sample data. In particular, we conduct further tests of our underlying hypotheses using momentum, size, and book-to-market measures only (i.e., testing null hypotheses $H3_0$, $H4_0$ and $H5_0$ respectively). Considering the effect of only these factors and excluding other factors, particularly INVEST_RELATE, enables us to establish whether the regulatory authorities are addressing potential problems of analyst stock recommendation bias fully by focusing principally on conflict of interest issues.[10] Should they also seek to review the important role of analyst cognitive bias which, may, in fact, be difficult to regulate?

[10] Content analysis of analysts' reports was only conducted for nonconforming stocks; similarly with target prices as these were obtained from analyst reports.

Our two samples again consist of all new buy stocks which underperform the relevant benchmark by at least <-20%, and all new sell stocks that outperform the relevant benchmark by at least >+20%, and that meet all necessary data requirements. Because, in this case, there is no restriction imposed by the lack of availability of analyst research reports, our samples can be far larger compared to those in the previous sub-section i.e., 1,349 new buys and 429 new sells.

We use a scaled-down version of the previous logit model (equation 2) to predict which measures of representativeness bias are significant in differentiating between nonconforming new buy and new sell recommendations. Our second logit model (equation 3) regresses the dependent variable RATING against the independent variables momentum (PRICE_MOM), size (FIRM_SIZE), and book-to-market (BTOM), proxying for different aspects of representativeness bias, and the control variable measuring analyst following (ANALY_FOLL). Again, RATING = 1 if an analyst issues a new buy recommendation which subsequently underperforms the benchmark by <- 20%, and 0 if a new sell recommendation outperforms the benchmark by >+20%. The following logistic regression model is fitted:

$$\begin{aligned} \text{RATING} = \text{LOGIT}(\pi) &= \text{LN}\left(\frac{\pi}{1-\pi}\right) \\ &= \alpha + \beta_1 \text{PRICE\_MOM}_{j,t-1} + \beta_2 \text{FIRM\_SIZE}_{j,t-1} \\ &+ \beta_3 \text{BTOM}_{j,t-1} + \beta_4 \text{ANALY\_FOLL}_{j,t-1} + \varepsilon_{j,t} \end{aligned} \tag{3}$$

where PRICE_MOM, FIRM_SIZE, BTOM and ANALY_FOLL are independent variables for firm j, $\beta_1 \ldots\ldots \beta_4$ are the regression parameter estimates, and $\varepsilon_{j,t}$ is the error term.

Table 8 reports the results from running equation 3. It shows that PRICE_MOM and BTOM are the two measures of representativeness bias which are individually significant in differentiating between new buy underperformers and new sell outperformers; both are significant at p<.001. The significance of PRICE_MOM and BTOM can be interpreted as indicating that the previous price performance of the firm and the firm's growth stock status are being viewed by analysts as representative of what the future performance of the firm should be. However, there is no significant difference in size of firm between those buy and sell recommendations that perform contrary to expectations (nonconforming stocks).[11] The approximate model explanatory paper is 6%, and the model is significant at better than the 0.01% level. On this basis, we are again forced to reject at least null hypotheses $H3_o$ and $H5_o$ at conventional levels, consistent with analyst cognitive bias being an important driver of their investment recommendations for stocks that subsequently perform perversely.

Table 8 here

In addition to investigating whether factors associated with representativeness bias distinguish between nonconforming new buys and nonconforming new sells we perform further analysis by comparing the characteristics of all "wrong" new buys with the remaining population of buy recommendations and similarly for new sells. In other words we compare the characteristics of all new buys (sells) that underperform (outperform) the benchmark with those that perform in line with expectations and outperform (underperform) the benchmark.[12] Specifically, we re-run equation 3 two more times with the same independent variables as before. The dependent variable RATING = 1 in the first (second) case if the new buy (sell) recommendation strictly underperforms (outperforms) the benchmark and 0 otherwise. Our results are presented in Table 9. Model A relates to the comparison of those buy recommendations whose subsequent 12-month stock returns are lower than the respective benchmark return vs. those buy recommendations that are associated with returns greater than the benchmark return. Model B relates to the comparison of those sell recommendations whose subsequent 12-month stock returns are greater than the respective benchmark return vs. those sell recommendations that generated returns lower than the benchmark return.

Table 9 here

[11] The control variable ANALY_FOLL is also highly significant ($p<0.1\%$) in predicting analysts' nonconforming ratings.
[12] The number of cases is presented in columns 2 and 3 of table 4.

Model A in Table 9 indicates that those new buy recommendations with returns below the benchmark have significantly higher previous stock-price momentum (PRICE_MOM) and are of larger size (SIZE) than those that outperform the benchmark. However, though the coefficient on BTOM is negative, in line with expectations, it is not statistically significant.

Interestingly, in the case of model B, where we compare the characteristics of outperforming new sell recommendations, with all "correctly" performing sell recommendations, only SIZE is significant. However, in contrast to the model A results, the likelihood ratio itself is not significant suggesting that factors associated with representativeness bias are not important in differentiating between conforming and nonconforming new sell recommendations. We speculate that analysts' decision processes in the case of new sell recommendations may be less cognitively biased and be driven more by fundamental analysis. By their nature sell recommendations are less frequent and more visible than buy and hold recommendations. Therefore an incorrect judgment in this case is likely to be more costly to an analyst's reputation than an incorrect judgment on a buy recommendation when other analysts are likely to be making similar stock recommendations (Womack, 1996). The reduced evidence of impact of cognitive biases in the case of new sell recommendations is consistent with the discussion of table 4 in section 5.2 above, which shows new sell recommendations perform more in line with analyst expectations than do their new buy equivalents.

7. Conclusions

In this study, we start by evaluating the performance of new buy and new sell stock recommendations over the 12 months subsequent to recommendation change. The aim is to establish whether stocks perform as expected or contrary to expectations, and to allow us to select those stocks that perform perversely for further analysis. Consistent with prior research (e.g., Stickel, 1995, Womack, 1996 and Barber et al. 2001) we find that the market does react to changes in stock recommendations. However, in the case of new buys, market reaction is complete by the end of the month in which the recommendation is issued, while, in contrast, the market continues to react up to a year to new sell recommendations. We also find a large proportion of new buy and new sell recommendations do not perform as predicted by analysts, particularly new buy recommendations.

We investigate factors that might be driving these analyst judgment calls that turn out subsequently to be wrong. Our logistical regression results show that the probability that analysts will issue a buy recommendation that underperforms the respective benchmark in a major way increases with degree of analyst optimism (a proxy for overconfidence bias). This is consistent with analysts believing they have superior investment abilities, leading them to overestimate the likely performance of the stocks they follow. This argument parallels that in other studies, such as Odean (1998a, 1998b), Barber and Odean (2001), and Massey and Thaler (2005), who document that when investors are faced with difficult tasks they tend to overestimate the precision of their information and thereby become overconfident.

In addition to optimism, three measures of representativeness bias, positive prior returns, firm size, and book-to-market are individually statistically significant in explaining analysts' nonconforming stock recommendations. These results suggest that stock characteristics are very important for analyst decision-making regarding the future performance of the stocks they follow. Our findings echo the conclusions of Stickel (2000), and Jegadeesh et al. (2004), that analysts prefer stocks with "best" characteristics.

Importantly, potential conflicts of interest are also found to have a significant impact on the type of recommendations that analysts issue, as measured by investment banking relationships with the firm the analyst is following. These findings are consistent with the findings of Lin and McNichols (1998) and other studies (e.g., Barber et al. 2004; Cliff, 2004; Agrawal and Chen, 2005; and Madureira, 2004) that have been conducted after the implementation of various rules meant to control analyst behavior. All these studies conclude that the relationships between brokerage houses and firms have an effect on analysts' stock ratings. Such results further confirm the recent concern by policy-makers and investors that analysts' recommendations do not necessarily reflect their true beliefs about the stocks they follow. Further, these findings justify recent regulations governing analyst and brokerage firm activity.

In further analysis we find that analyst representativeness bias appears to be more manifest in their new buy recommendations than in their new sell recommendations. We argue that this is consistent with analysts making sell recommendations only after a more thorough fundamental analysis than they do for their new buy equivalents. Analysts have incentives to be more careful in making sell recommendations as an "incorrect" sell may be more costly to an analyst's reputation as they are less frequent and hence more visible.

Rules implemented to date only effectively seek to address the optimism in analysts' recommendations arising from the corporate relationships that investment banks have with firms, suggesting that the SEC and others believe that the problem of optimistic stock recommendations is predominantly caused by analyst incentives associated with conflict of interest issues. This study addresses the problem of optimistic recommendations from a broader perspective and shows that there are other factors over and above conflicts of interest that are contributing to this problem, in particular, analyst cognitive bias, which is arguably inherent in the analyst's job and may, in fact, be difficult to regulate. Such bias seems to be more manifest in analysts' new buy recommendations than in their new sell counterparts suggesting that analysts' buy recommendations in particular will continue to lack investment value notwithstanding the enacted regulatory changes.

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Figure 1: Distribution of new buys, holds and sells between January 1997 and December 2003 by year

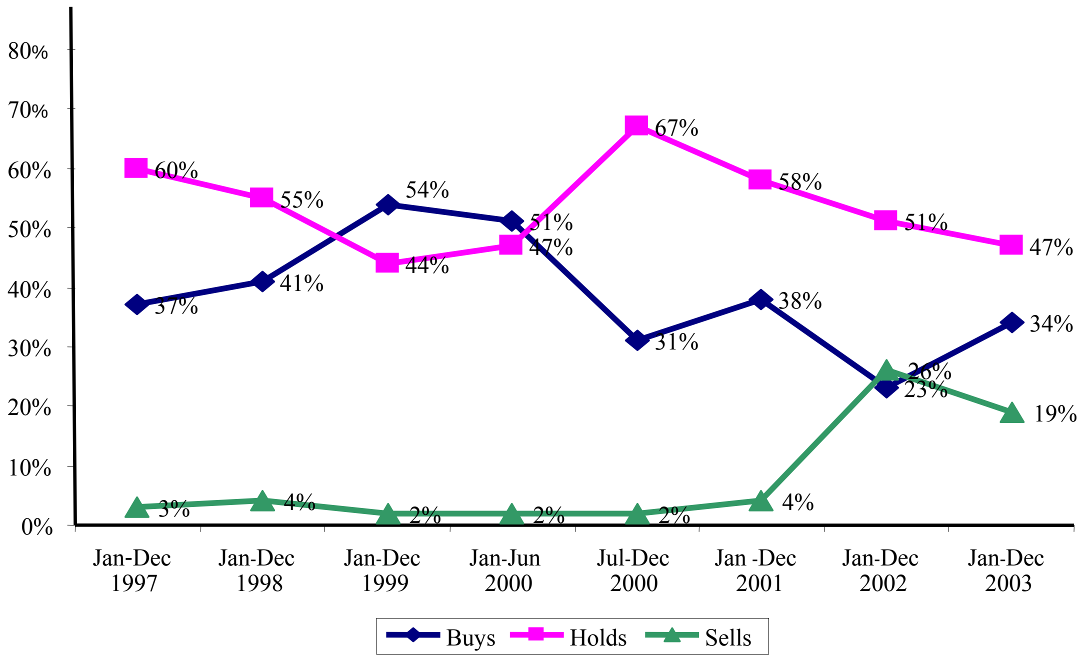

Figure 2: Mean BHARs for new buy and new sell recommendations

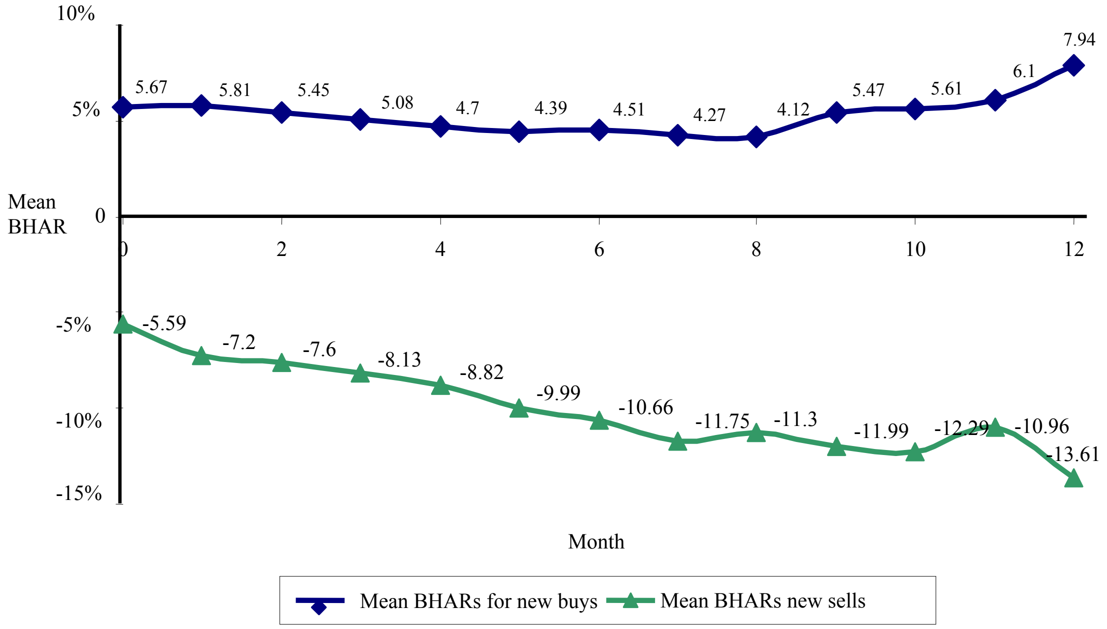

Table 1: Sample selection process – stock recommendations

Procedure	Number of observations
Total stock recommendations available in the *IBES* database	363,158
Less recommendations made by non-top-ten brokerages	252,062
Recommendations by the top-ten brokers	111,096
Less recommendations issued before Jan 1, 1997 and after Dec 31, 2003	30,886
Recommendations issued between Jan 1, 1997 and Dec 31, 2003	80,210
Eliminating reiterations by the same or other analysts	60,046
Excluding utilities and financials[1]	20,164
Total excluding utilities and financials	3,966
Eliminating US and non-US stocks with no data in CRSP	16,198
Total recommendation changes	2,029
	14,169

[1]Financial and utility firms are excluded from the analysis because of the unique nature of their enterprises.

Table 2: Transition matrix of recommendation changes

This table presents the transition matrix of changes in recommendation for our entire sample period, January 1, 1997 to December 31, 2003. Old rating denotes the previous stock rating and new rating the current category. The transition percentages are shown in brackets.

	New rating				
Old Rating	Buy	Hold	Sell	Total	Total %
Buy	-	6508 (46%)	278 (2%)	6786 (48%)	48%
Hold	4739 (34%)	-	1630 (11%)	6369 (45%)	45%
Sell	149 (1%)	865 (6%)	-	1014 (7%)	7%
Total	4888	7373	1908	14169	-
Total %	(35%)	(52%)	(13%)		100%

mean ratio of buys to sells = 2.6:1

Table 3: Performance of new buy and sell recommendations

This table provides the buy-and-hold (BHAR) event returns for new buy and new sell recommendations. Column 1 provides the performance period, columns 2-5 provide the BHAR mean, median, t-statistics and sign for the samples of buy and sell recommendations. Column 6 provides the number of firms existing over the 12-month horizon.

****, ***, **, and * denote significance at .01%, 1%, 5% and 10% levels, respectively.

Panel A: performance of new buy recommendations

Period	BHAR mean (%)	BHAR median (%)	t-statistics	Sign test M-statistic[1]	Live firms
Month 0	5.67	3.53	13.53****	262****	2232
Month 1	5.81	3.37	10.70****	176****	2225
Month 2	5.45	2.42	8.33****	104****	2213
Month 3	5.08	1.60	6.67****	58****	2202
Month 4	4.70	0.68	5.37****	24	2188
Month 5	4.39	0.42	6.74****	16	2182
Month 6	4.51	-0.71	4.55****	-20	2174
Month 7	4.27	-1.62	3.78****	-54	2159
Month 8	4.12	-2.98	3.21****	-88****	2153
Month 9	5.47	-3.77	3.53****	-98****	2144
Month 10	5.61	-5.28	3.16****	-125****	2132
Month 11	6.10	-5.39	2.95***	-122****	2123
Month 12	7.94	-4.97	3.74****	-104****	2109

Panel B: performance of new sell recommendations

Period	BHAR mean (%)	BHAR median (%)	t-statistics	Sign test m-statistic[1]	Live firms
Month 0	-5.59	-4.34	-6.80****	-93****	1067
Month 1	-7.20	-5.80	-7.70****	-105****	1063
Month 2	-7.60	-8.11	-5.90****	-96****	1056
Month 3	-8.13	-8.31	-5.69****	-97****	1050
Month 4	-8.82	-8.57	-6.27****	-103****	1043
Month 5	-9.99	-10.80	-6.50****	-111****	1039
Month 6	-10.66	-11.39	-7.56****	-101****	1032
Month 7	-11.75	-13.16	-7.31****	-101****	1022
Month 8	-11.30	-15.90	-5.60****	-110****	1019
Month 9	-11.99	-16.25	-5.31****	-119****	1012
Month 10	-12.29	-18.15	-4.60****	-128****	1003
Month 11	-10.96	-19.60	-3.70****	-128****	996
Month 12	-13.61	-19.86	-4.65****	135****	988

[1]The statistic M is defined to be **$M = (N^+ - N^-)/2$** where N^+ is the number of values that are greater than μ_o and N^- is the number of values that are less than μ_o. Values equal to μ_o are discarded. Under the hypothesis that the population median is equal to μ_o, the sign test calculates the p-value for M using a binomial distribution. The test is based on the null hypothesis that the population median equals μ_o. The default value in for μ_o is 0.

Table 4: Performance of new buy and sell recommendations over time and selection of nonconforming stock recommendations

This table shows how stocks with new buy/sell recommendations perform over the subsequent 12-month period. Column 1 gives the month after the change is made. Column 2 shows the number of firms with performance in the expected direction. Column 3 shows the number of firms with performance in an unanticipated direction. Column 4 shows the number and percentage of buy/sell recommendations yielding returns of at least 10% (-10%) as per brokerage firms' definition of recommendations. Columns 5-8 provide the number and percentage of recommendations with abnormal returns in the extreme opposite to the expectation i.e., below/above 10% (-10%) and 20% (-20%).

Panel A: Performance of new buy recommendations over time
N = 2232

Month	No. of firms with positive return (BHAR > = 0)	No. of firms with negative return (BHAR < 0)	Expected outperformance		Unexpected underperformance			
			BHAR > = 10%		BHAR = < -10 %		BHAR = <-20 %	
			n	%	n	%	n	%
0	1378	854	535	32.89	354	15.86	121	5.42
1	1292	940	604	36.65	495	22.17	221	9.90
2	1220	1012	662	37.05	575	25.76	321	14.38
3	1174	1058	655	35.71	659	29.52	383	17.15
4	1139	1092	662	36.78	726	32.52	446	19.98
5	1135	1097	669	36.42	832	37.27	558	25.00
6	1096	1136	689	36.38	843	37.76	550	24.64
7	1062	1170	697	36.34	881	39.47	591	26.47
8	1028	1204	697	35.89	914	40.94	643	28.80
9	1018	1214	697	35.75	922	41.30	658	29.48
10	991	1241	695	34.86	963	43.14	696	31.18
11	994	1238	701	35.08	973	43.59	749	33.55
12	991	1220	698	34.68	996	44.62	759	34.00

Panel B: Performance of new sell recommendations over time
N = 684

Month	No. of firms with negative return (BHAR < 0)	No of firms with positive return (BHAR > = 0)	Expected underperformance		Unexpected outperformance			
			BHAR < = -10 %		BHAR > 10 %		BHAR >20 %	
			n	%	n	%	n	%
0	435	249	225	32.89	93	13.59	44	6.43
1	447	237	286	41.81	129	18.85	68	9.94
2	438	246	312	45.61	131	19.15	75	10.96
3	439	245	317	46.35	139	20.32	83	12.13
4	445	239	331	48.39	151	22.07	87	12.71
5	440	244	349	51.02	171	25.00	130	19.00
6	443	241	368	53.80	160	23.39	108	15.78
7	443	241	373	54.53	159	23.24	102	14.91
8	452	232	375	54.82	147	21.49	103	15.05
9	461	223	388	56.73	145	21.19	102	14.91
10	470	214	391	57.16	141	20.61	109	15.93
11	470	214	393	57.46	153	22.36	120	17.54
12	477	207	401	58.63	150	21.92	111	16.22

Table 5: Characteristics of nonconforming new buy and new sell recommendations

The table provides statistics on the characteristics of nonconforming new buy and new sell recommendations that are issued between January 1, 1997 and December 31, 2003. Column 1 shows the variables, and columns 2-11 provide the mean, 1st quartile, median, 3rd quartile, standard deviation, kurtosis, skewness, highest and lowest extreme values and mean difference between the two samples. ****, ***,**, * denote significance at 0.1%, 1%, 5% and 10% respectively.

Panel A: Underperforming new buy recommendations
N = 261

Model variables[1]	Mean	1st quartile	Median	3rd quartile	Standard deviation	Kurtosis	Skewness	Extreme values		(mean buy-mean sell) Mean difference	
								Lowest	Highest		
OPTIMISM	51.38	50.22	51.25	52.56	2.48	3.93	-0.26	38.46	61.35	0.843	*
CERTAINTY	50.63	49.37	50.57	51.72	2.01	2.26	0.13	41.45	58.60	-0.004	
ACTIVITY	47.75	47.15	48.99	50.47	6.58	51.53	-6.05	-21.29	54.88	0.792	
PRICE_MOM	0.018	-0.010	0.016	0.041	0.054	2.010	0.029	-0.185	0.174	0.033	****
FIRM_SIZE (LN)	7.94	6.75	7.81	8.98	1.64	-0.16	0.35	3.81	12.10	0.940	****
FIRM_SIZE (RAW)	11,816	861	2,480	7,978	28236	19.836	4.287	45	181,286	8620	****
BTOM	0.368	0.104	0.257	0.458	0.478	33.187	4.746	0.001	4.508	-0.626	****
INVEST_RELATE	0.95	0	1	2	0.77	-1.31	0.07	0	2	0.225	**
ANALY_FOLL	30	19	27	39	15	0.111	0.811	6	100	5.789	****
TGTPRCE_CHNG	0.16	-0.07	0.06	0.20	0.59	51.20	5.77	-0.74	6.28	0.298	****

Panel B: Outperforming new sell recommendations
N = 71

Model variables[1]	Mean	1st quartile	Median	3rd quartile	Standard deviation	Kurtosis	Skewness	Extreme values		(mean buy-mean sell) Mean difference	
								Lowest	Highest		
OPTIMISM	50.54	48.84	50.32	51.85	2.43	0.47	0.56	44.64	56.85	0.843	*
CERTAINTY	50.63	49.24	50.55	51.92	2.42	4.27	1.03	45.44	61.19	-0.004	
ACTIVITY	48.56	47.02	48.50	50.29	3.54	10.84	0.60	33.84	65.86	0.792	
PRICE_MOM	-0.015	-0.045	-0.009	0.019	0.057	0.717	-0.058	-0.146	0.160	0.033	****
FIRM_SIZE (LN)	7.00	6.08	7.15	8.14	1.63	-0.22	-0.33	2.98	10.26	0.940	****
FIRM_SIZE (RAW)	3,195	439	1,284	3,434	5,090	9.82	2.91	19.88	28,600	8620	****
BTOM	0.995	0.317	0.506	0.958	1.502	10.128	3.212	0.051	7.514	-0.626	****
INVEST_RELATE	0.73	0	1	1	0.60	-0.53	0.21	0	2	0.225	**
ANALY_FOLL	24	13	24	33	13	-0.24	0.464	2	60	5.789	****
TGTPRCE_CHNG	-0.14	-0.33	-0.16	-0.02	0.37	6.95	1.66	-0.90	1.60	0.298	****

Table 5 (… cont)

[1]Variable definitions

$OPTIMISM_{j,t}$	=	a content analysis (*Diction* score) variable indicating endorsement of some person, group, concept or event, or highlighting their positive entailments as captured in the language used by the analyst when changing firm *j*'s stock rating. This variable serves as a proxy for analyst overconfidence;
$CERTAINTY_{j,t}$	=	a content analysis (*Diction* score) variable indicating resoluteness, inflexibility and completeness in the language used by an analyst when changing firm *j*'s stock rating. This variable serves as a proxy for analyst overconfidence;
$ACTIVITY_{j,t}$	=	a content analysis (*Diction* score) variable indicating movement, change and the implementation of ideas and the avoidance of inertia as captured in the language used by an analyst when changing firm *j*'s stock rating. This variable serves as proxy for analyst representativeness bias;
$PRICE\_MOM_{j,t-1}$	=	firm j's percentage change in stock price over year t computed as stock price at time t/stock price at time t-1 expressed on an average monthly basis;
$FIRM\_SIZE\ (LN)_{j,t-1}$	=	firm size in million dollars, measured using the natural logarithm of the market value of equity for firm *j* at the end of the year preceding the change of recommendation;
$FIRM\_SIZE\ (RAW)_{j,t-1}$	=	firm size in million dollars, measured as a the market value of equity for firm *j* at the end of the year preceding the change of recommendation;
$BTOM_{j,t-1}$	=	firm *j*'s book value per share divided by market value of equity per share at the end of the year preceding the change in recommendation;
$INVEST\_RELATE_{j,t}$	=	a variable that takes a value of 0 if there is no relationship between the analyst's brokerage firm and the firm, 1 if the brokerage is an underwriter of the firm or has current holdings in the firm, and 2 if the brokerage is both an underwriter and has current holdings;
$ANALY\_FOLL_{j,t-1}$	=	the number of analysts (for all brokerage firms available on *IBES*) following the firm in the calendar year that firm *j*'s recommendation is changed;
$TGTPRCE\_CHNG_{j,t}$	=	the percentage change in analyst projected 12 month target price for firm j computed as [(price target at time t / price target at time t – 1) – 1].

Table 6: Pearsonian product – moment correlation coefficients

This table presents the correlation matrix for the following variables: $OPTIMISM_{j,t}$ is a content analysis (*Diction* score) variable indicating endorsement of some person, group, concept or event or highlighting their positive entailments as captured in the language used by the analyst when changing firm *j*'s stock rating - this variable serves as a proxy for analyst overconfidence; $CERTAINTY_{j,t}$ is a content analysis (*Diction* score) variable indicating resoluteness, inflexibility and completeness in the language used by an analyst when changing firm *j*'s stock rating - this variable serves as a proxy for analyst overconfidence; $ACTIVITY_{j,t}$ is content analysis (*Diction* score) variable indicating movement, change and the implementation of ideas and the avoidance of inertia as captured in the language used by an analyst when changing firm *j*'s stock rating - this variable serves as a proxy for analyst representativeness bias; $PRICE\_MOM_{j,t-1}$ is firm j's percentage change in stock price over year t computed as stock price at time t/stock price at time t-1 expressed on an average monthly basis; $FIRM\_SIZE_{j,t-1}$ is firm size in million dollars measured using the natural logarithm of the market value of equity for firm *j* at the end of the year preceding the change of recommendation; $BTOM_{j,t-1}$ is firm *j*'s book value per share divided by market value of equity per share at the end of the year preceding the change in recommendation. $INVEST\_RELATE_{j,t}$ is a variable that takes a value of 0 if there is no relationship between the analyst's brokerage firm and the firm, 1 if the brokerage is an underwriter of the firm or has current holdings in the firm, and 2 if the brokerage is both an underwriter and has current holdings; $ANALY\_FOLL_{j,t-1}$ is the number of analysts (for all brokerage firms available on *IBES*) following the firm in the calendar year that firm *j*'s recommendation is changed. P-values are listed below the correlation coefficient, and $TGTPRCE\_CHNG_{j,t}$ is the percentage change in analyst projected target price for firm j computed as [(price target at time t / price target at time t -1) –1]. ****, ***, **, and * denote significance at 0.1%, 1%, 5%, and 10% levels respectively.

Table 6 (…cont)

	OPTIMISM	CERTAINTY	ACTIVITY	PRICE_MOM	FIRM_SIZE	BTOM	INVEST_RELATE	ANAL_FOLL
CERTAINTY	0.1366 (0.0127)**							
ACTIVITY	-0.0975 (0.0758)*	0.1353 (0.0136)**						
PRICE_MOM	0.0755 (0.1714)	0.0389 (0.4817)	0.0853 (0.1222)					
FIRM_SIZE	0.1239 (0.0252)**	-0.0059 0.9153	-0.0633 (0.2542)	-0.0557 (0.3154)				
BTOM	-0.1679 (0.0023)****	-0.0673 (0.2250)	0.0461 (0.4061)	-0.1214 (0.0284)**	-0.4008 (0.0001)****			
INVEST_RELATE	0.0403 (0.4639)	0.0587 (0.2866)	0.0639 (0.2458)	0.0191 (0.7294)	0.0248 (0.6549)	-0.0719 (0.1955)		
ANALY_FOLL	0.0833 (0.1298)	-0.0198 (0.7181)	-0.066 (0.2262)	0.0070 (0.8993)	0.7639 (0.0001)****	-0.2927 (0.0001)****	-0.0253 (0.6463)	
TGTPRCE_CHNG[2]	0.0692 (0.2226)	0.0702 (0.2162)	0.0272 (0.6315)	0.2451 (<.0001)****	0.0585 (0.3062)	-0.1065 (0.0622)*	0.0139 (0.8071)	0.1080 (0.0567)**

[2]The correlation between change in target price (TGTPRCE_CHNG) and RATING is significant at the 0.1% level.

Table 7: Determinants of new buy/sell recommendations for nonconforming stocks

This table presents the logit regression on all model and control variables. The logit regression model is as shown in equation 2. The dependent variable is the stock rating. For each variable included in the model, the predicted sign, coefficient estimate, Wald χ^2 and odds ratio (EXP (β)) are presented in columns 2-5 respectively. R^2, likelihood ratio and number of observations the regression are provided. The dependent variable RATING is a dummy variable that takes the value of 1 if the recommendation is an nonconforming new buy, and 0 if the recommendation is a nonconforming new sell. The independent variables are, as shown in table 5. ****,***, **, and * denote significance at 0.1% 1%, 5% and 10% levels, respectively.

Independent variable	Predicted sign for buys	Parameter Estimates	Wald χ^2	EXP (β)
INTERCEPT	?	-3.112	0.388	-
OPTIMISM	+	0.107	2.758*	1.114
CERTAINTY	+	-0.053	0.534	0.948
ACTIVITY	-	-0.015	0.179	0.985
PRICE_MOM	+	12.217	13.50****	>999.999
FIRM_SIZE	+	0.331	3.867**	1.938
BTOM	-	-0.508	3.102*	1.059
INVEST_RELATE	+	0.592	6.113***	2.892
ANALY_FOLL	+	-0.009	0.334	1.024
TGTPRCE_CHNG	+	1.926	11.609****	20.79
Maximum rescaled R^2	19%			
Likelihood ratio χ^2	64.57****			
N	332			

The Wald statistics are distributed χ^2 with 1 degree of freedom.

Table 8: Factors that differentiate between nonconforming new buy and new sell recommendations: the role of representativeness bias

This table presents the logit regression on behavioral factors which potentially differentiate between nonconforming new buy and new sell recommendations. For each variable, the predicted sign, coefficient estimate, Wald χ^2 and odds ratio (EXP(β)) are presented in columns 2-5 respectively. R^2, likelihood ratio and number of observations in the regression are also provided. The dependent variable RATING is a dummy variable that takes the value of 1 if the recommendation is a nonconforming new buy and 0 if the recommendation is a nonconforming new sell. The independent variables are as shown in table 5. ****,***, **, and * denote significance at 0.1% 1%, 5% and 10% levels, respectively.

Independent variable	Predicted sign for buys	Parameter estimates	Wald χ^2	EXP (β)
Intercept	?	0.818	6.169****	-
PRICE_MOM	+	8.223	54.623****	>999.999
FIRM_SIZE	+	0.031	0.358	1.031
BTOM	-	-0.290	17.509****	0.748
ANALY_FOLL	+	0.010	3.500****	1.010
Maximum rescaled R^2	6%			
Likelihood ratio χ^2	109.08****			
N	1,778			

The Wald statistics are distributed χ^2 with 1 degree of freedom.

Table 9: Factors that differentiate between underperforming (outperforming) new buy (new sell) recommendations and all other buy (sell) recommendations during the sample period: the role of representativeness bias

This table presents the logit regression on behavioral factors which potentially differentiate between those new buy (sell) recommendations with subsequent performance below (above) the respective benchmark with those new buy (sell) recommendations with subsequent performance greater (less) than the benchmark returns. For each variable, the predicted sign, coefficient estimate, Wald χ^2 and odds ratio (EXP(β)) are presented in columns 2-5 for new buys (columns 6-9 for new sells) respectively. R^2, likelihood ratio χ^2, and number of observations in the regression is provided below the variables. For model A, RATING = 1 if the new buy recommendation underperforms the benchmark return and 0 if the new buy recommendation outperforms the benchmark return. For model B, RATING = 1 if the new sell recommendation outperforms the benchmark return and 0 if the new sell recommendation underperforms the benchmark return. The independent variables are as shown in table 5. ****,***, **, and * denote significance at 0.1% 1%, 5% and 10% levels, respectively.

	Model A				Model B			
Independent variable	Predicted sign for buys	Parameter Estimates	Wald χ^2	EXP (β)	Predicted sign for sells	Parameter Estimates	Wald χ^2	EXP (β)
Intercept	?	-1.071	17.521****	-	?	0.364	0.473	-
PRICE_MOM	+	0.029	11.069****	1.030	-	-0.004	0.071	0.995
FIRM_SIZE	+	0.235	37.856****	1.265	-	-0.178	4.254**	0.836
BTOM	-	-0.050	0.417	0.951	+	-0.007	0.008	0.993
ANALY_FOLL	+	0.019	23.702****	0.981	-	0.0043	0.225	1.004
Maximum rescaled R^2		3.37%				1.60%		
Likelihood ratio χ^2		55.73****				7.39		
N		2211				684		

The Wald statistics are distributed χ^2 with 1 degree of freedom.