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Behavioural Bias and Conflicts of Interest in Analyst Stock Recommendations

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Abstract: This paper tests whether sell-side analysts are prone to behavioural errors when making stock recommendations as well as the impact of investment banking relationships on their judgments. In particular, we analyse their report narratives for evidence of cognitive bias. We find first that new buy recommendations on average have no investment value whereas new sell recommendations do, and take time to be assimilated by the market. We also show that new buy recommendations are distinguished from new sells both by the level of analyst optimism and representativeness bias as well as with increased conflicts of interest. Successful new buy recommendations are characterised by lower prior returns, value stock status, smaller firms and weaker investment banking relationships. On the other hand, successful new sells do not differ from their unsuccessful counterparts in terms of these measures. As such, we provide evidence that analysts are prone both to behavioural bias as well as potential conflicts of interest in their new buy stock recommendation decisions. We also show that these two explanations of analyst behaviour are to a great extent independent of each other. Consequently, the recent attempts by regulators to address potential conflicts of interest in analyst behaviour may have only limited impact.

Keywords: stock recommendations, analysts' incentives, behavioural finance, conflicts of interest, content analysis

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1. INTRODUCTION

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 sell-side 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) introduced Regulation Fair Disclosure (Reg FD). Reg FD was meant to curb the practice of asymmetric information provision whereby top executives would disclose information to particular analysts, often to those working for the investment banks with which 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. 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 $1.4 billion 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 due only to 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, as Brown and Pfieffer (2008) also demonstrate in the case of investment strategies based on analysts' earnings forecasts. On the other hand, whereas Womack (1996) finds some evidence of stock outperformance over the one month period subsequent to a new buy recommendation, far stronger are his results of continuing downward drift in stock prices over the following six months associated with the small number of new sells. Such research findings lead to the question of why most analyst stock recommendations lack investment value.

In our study of the relative importance of cognitive bias and conflicts of interest in determining analyst behaviour, we focus specifically on stock recommendations rather than earnings forecasts. This is both because regulators are primarily concerned with the former due to how unsophisticated investors use these (e.g., Mikhail et al., 2007; and Malmendier and Shanthikumar, 2007), and the evidence that analysts have greater economic incentives to bias their stock recommendations than their earnings forecasts (e.g., Irvine, 2004). In addition, the two should be correlated (e.g., Eames et al., 2002; Bradshaw, 2004; and Asquith et al., 2005).

This paper argues that an important determinant of the apparent judgmental errors made by analysts is also cognitive bias. Although there are various cognitive biases documented in the behavioural finance literature, three salient biases recognised as key in explaining the 'irrational' behaviour of market participants are overoptimism, overconfidence and representativeness.

One of the most robust findings in the psychology of intuitive judgement is that people's predictions tend to be optimistically biased (e.g., see the review in Armor and Taylor, 2005). Overoptimism is the tendency to overestimate the likelihood of desired outcomes and underestimate the frequency of unfavourable events and is one of the most cited biases in the literature on analysts' forecasts and recommendations (see, for example, Ramnath et al., 2008). For example, Eastwood and Nutt (1999) document that analysts both underreact to negative information and overreact to positive information which behaviour they conclude is consistent with analysts systematically reacting in an optimistic manner. Similarly, Eames et al. (2002) find that analysts' earnings forecast errors are significantly optimistic for buy recommendations and significantly pessimistic for sell recommendations, again consistent with overoptimism bias.

However, it should be pointed out that optimistic analyst behaviour is also consistent with their economic incentives and thus potential conflicts of interest. This might include using optimistic forecasts and stock recommendations to curry favour with management and thus access to private information (e.g., Francis and Philbrick, 1993; Hodgkinson, 2001; and Conrad et al., 2006), motivate stock trades and thus higher trading commissions (e.g., Irvine, 2004; Jackson, 2005; and Cowen et al., 2006),[1] enhance career progression, which Hong and Kubrick (2003) demonstrates is associated more with earnings forecast optimism than with accuracy, and to obtain or maintain investment banking business, a particular focus of this paper (e.g., Dugar and Nathan, 1995; Lin and McNichols, 1998; and O'Brien et al., 2005).

Another important behavioural finding is that people are typically overconfident about their knowledge when the issues at hand are difficult (Shefrin, 2008, p. 58). This leads them to underestimate risk because they put too much weight on the information they collect themselves and hence the reliability of their judgements (Daniel et al., 1998). The more difficult the decision task, and the more complex it is, the more successful we expect ourselves to be. Overconfidence may thus help 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, Barber and Odean (2000) look at the buying and selling activities of individual investors at a discount brokerage and find the more they trade the more they underperform relevant benchmarks. Although liquidity demands, risk management, and tax considerations may explain some of this activity, nonetheless, the authors argue the only plausible explanation for why investors trade to their detriment is overconfidence. Overconfident investors overestimate the precision of their private information and thereby the expected gain of trading (Daniel et al., 1998).

The representativeness heuristic (Tversky and Kahneman, 1974) involves making judgments based on stereotypes rather than on the underlying characteristics of the

1 In addition, analysts generate greater trading commissions with buy than sell recommendations as the population of investors holding a particular stock is smaller than the population of potential purchasers and many funds, as well as retail investors, are constrained from short-selling.

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. Shefrin and Statman (2003) show that investors believe that 'good' stocks are stocks of 'good' companies, i.e., large, low book-to-market, and high prior return firms, although their evidence on subsequent stock performance is inconsistent with this. Similarly, Jegadeesh et al. (2004) show that sell-side analysts tend to recommend expensive, high growth 'glamour' stocks, even though such recommendations can be costly. Such seemingly contrarian behaviours are consistent with the operation of the representativeness bias.

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 stock market 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 continuing post-recommendation stock price downward drift of −8% in the subsequent 12 months over and above the 5.6% fall in the recommendation month.

We next establish which factors are associated with buy and sell recommendations. We find that analysts' new buy stock recommendations compared with new sells are associated with (i) overoptimism bias (as measured by the optimistic tone of language used in their research reports compared with subsequent lack of stock outperformance), (ii) representativeness bias (as measured by previous stock price performance, growth status of the firm (low book-to-market) and firm size, and (iii) corporate relationships between their investment bank employers and the firms they are following. In addition, we demonstrate that although analyst behavioural bias and conflicts of interest are largely independent, overoptimism is exacerbated if independence concerns are also present.

In further analysis, we compare the characteristics of successful new buy (sell) recommendations with those for stocks that miss the respective target benchmark over the next 12 months. In the case of new buys, those stocks which outperform the respective benchmark return by at least 10% are characterised by lower prior returns (momentum), 'value stock' status, lower analyst following and fewer investment banking relationships with the analyst's house. This suggests analyst stock recommendation errors may be associated with both the representativeness cognitive bias (the 'good company, good stock' syndrome) and potential conflicts of interest, whether conscious or unconscious. Importantly, we also demonstrate these two factors are, to a great extent, independent of each other. On the other hand, we find very limited evidence, if any at all, of parallel factors at work in the case of new sell recommendations.

Our findings imply that the regulations recently promulgated to govern analyst and brokerage house activity, however successful they might be in dealing with analysts' conflicts of interest, are likely to 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 subsequent performance of new buy and sell stock recommendations. Section 6 presents our main empirical results and concluding Section 7 discusses these and their implications.

2. HYPOTHESES

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

(i) Cognitive Biases

Tversky and Kahneman (1974) suggest 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, overoptimism, overconfidence and representativeness.

(a) Overoptimism Bias

We measure overoptimism bias by the tone of language that analysts use in their research reports. To do this we employ *Diction* (Hart, 2000), a computerised content analysis package.[2] *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.[3] To measure overoptimism we use the variable OPTIMISM provided by *Diction*. OPTIMISM is defined in *Diction* as language endorsing some person, group, concept or event or highlighting their positive entailment. 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 overoptimistic independent of whether the stock recommendation is new buy or new sell.

(b) Overconfidence Bias

As with overoptimism bias above, we measure overconfidence bias by the tone of language that analysts use in their research reports employing *Diction* (Hart, 2000). Following the arguments of Daniel et al. (1998), to measure overconfidence bias we use the *Diction* variable CERTAINTY to proxy for analyst estimates of the precision of their information. CERTAINTY is defined as language indicating resoluteness, inflexibility,

2 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.

3 These dictionaries were constructed by expert linguists from the analysis of more than 20,000 texts. Its automated nature both for coding and quantification makes it attractive as a research instrument (Sydserff and Weetman, 2002).

completeness and a tendency to speak *ex cathedra*. Our second null hypothesis is thus defined as follows:

$H2_0$: The tone of the language used by investment analysts in their research reports to justify their stock ratings is not overconfident independent of whether the stock recommendation is new buy or new sell.

If both overoptimism and overconfidence biases (as measured by OPTIMISM and CERTAINTY) influence analyst stock recommendations, then we expect both to have a significant positive (negative) impact on their new buy (sell) ratings for stocks that subsequently underperform analyst expectations.

(c) Representativeness Bias

Solt and Statman (1989) document that investors are prone to representativeness bias and argue that investors believe that past good performance and large market capitalisation are indicative of good future performance. Also analysts tend to prefer growth stocks to value stocks (Stickel, 2000), and value high levels of change in firm activities (Fogarty and Rogers, 2005). Accordingly, four independent variables measuring level of firm activity, prior returns, firm size, and growth status are constructed to proxy for any representativeness bias exhibited in analysts' decisions.

Activity: We first 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' stocks tend to be influenced by their knowledge of corporate plans, merger/acquisition talk, or any suggestion of change in corporate direction. Our third null hypothesis is therefore stated as follows:

$H3_0$: 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.

Previous price performance: Stickel (2000) posits that Wall Street 'darlings' are stocks with, among other characteristics, recent positive EPS momentum and surprise and 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 4 is therefore established as follows:

$H4_0$: Price momentum has no impact on analyst recommendations.

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 stock return over the year to the end of the calendar month immediately prior to the recommendation change date 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.

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 5 is therefore established as follows:

$H5_0$: Firm market capitalisation does not have any impact on the type of stock recommendation issued by analysts.

Variable FIRM_SIZE is used to pick up the effect of market capitalisation on the determination of buy and sell recommendations. As in Mikhail et al. (2004), firm size is measured using the natural logarithm of the market value of equity 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.

Book-to-market: Most buy recommendations are made by analysts who tend to favour '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 may be taken as representative of the stock's likely future performance by analysts. Null hypothesis 6 is therefore established as follows:

$H6_0$: The firm's book-to-market ratio does not have any impact on the type of recommendation issued by analysts.

Variable BTOM is used to capture the effect of book-to-market on analyst 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. 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.

(ii) 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 7 is therefore formulated as follows:

> $H7_0$: Corporate relationships between analysts' investment banks and particular firms have no bearing on the type of recommendations that analysts issue.

Two binary variables INVEST_RELATE1 and INVEST_RELATE2 are constructed to measure the relationship between the firm being researched and the investment bank which employs the analyst. INVEST_RELATE1 takes the value 1 if the brokerage house is an underwriter[4] of the firm *or* discloses current holdings[5] in the firm, and 0 otherwise. INVEST_RELATE2 takes the value 1 if the brokerage firm is *both* an underwriter *and* has current holdings, and 0 otherwise. Information about such relationships between firms and brokerage houses is hand collected from the disclosure section of analysts' research reports. Higher proportions of non-zero values of INVEST_RELATE1 and INVEST_RELATE2 are expected to be associated with new buys, and lower proportions 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*.

(iii) Control Variable: Analyst Following

We introduce analyst following as a control variable to ensure that our tests of the relationship between stock recommendation type and our cognitive bias and conflicts 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) observes 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. In particular, large firms have a larger analyst following than small firms. O'Brien and Bhushan (1990) also note that analyst following is higher for industries with regulated disclosures, and with larger numbers of firms. Lang and Lundhom (1996) document a positive association between analyst following and analyst forecast accuracy.

Our variable ANALY_FOLL represents by the total number of analysts following the firm taken from the Thomson Financial *Institutional Brokers' Estimate System* (*IBES)*. We postulate that there may be some indirect relationship between the number of analysts following the firm and the recommendation issued. In particular, higher values of ANALY_FOLL might be associated with new buy recommendations, and lower values with new sell recommendations.

3. DATA AND DESCRIPTIVE STATISTICS

The source of analysts' stock recommendations used in this research is the *IBES* detailed recommendation file.[6] To ensure we work with the larger houses where conflicts of

4 '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.

5 Current holding means the analyst report discloses holdings in the stock of the firm being researched by either the investment bank or its associate/s or at least one of its employees.

6 Ljungqvist et al. (2008) document *ex post* changes to the IBES analyst stock recommendations database during the period covered by this research. However, Glushkov (2007) points out these changes

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
	20,164
Excluding utilities and financials[1]	3,966
Total excluding utilities and financials	16,198
Eliminating US and non-US stocks with no data in CRSP	2,029
Total recommendation changes	14,169

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

interests are more likely to exist, our sample covers stock recommendations for the period from January 1, 1997 to December 31, 2003 issued by the top 10 US brokerage firms as identified in the December 2001 issue of the *Institutional Investor* survey of institutional investors. Sample selection on this basis additionally ensures the stock recommendation information is readily available to the market (Womack, 1996; and Ryan and Taffler, 2006) and reflects previous evidence that recommendations of large brokerage houses have greater investment impact (Stickel, 1995; Womack, 1996; and Green, 2006). Restricting the sample to top 10 houses also helps us to focus on the controversial role of the largest US brokerage firms in the financial markets and their stock recommendations.

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; Ryan and Taffler, 2006; and Barber et al., 2006), 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.

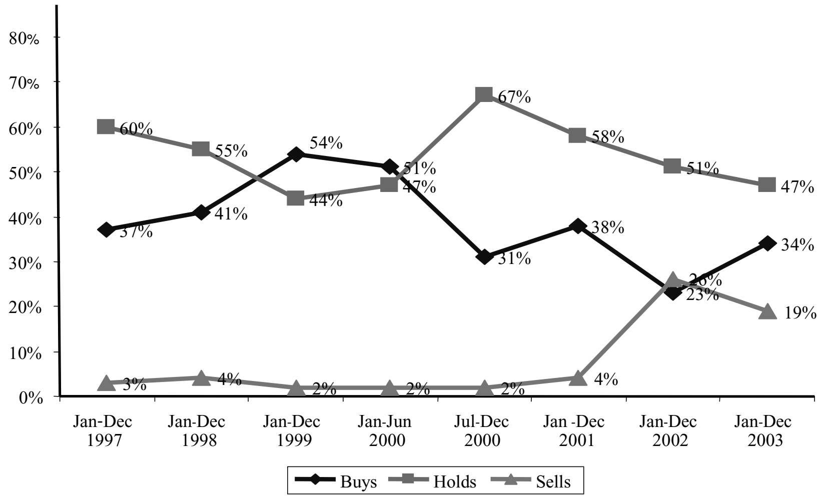
Only changes in recommendations and not reiterations are employed in this study because changes in recommendations have higher information content than reiterations (e.g., Womack, 1996; and Francis and Soffer, 1997). Changes examined are new buy recommendations following previous sells or holds, and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

predominantly relate to non-US brokerage houses and a careful reading of the Appendix to Ljungqvist et al. suggests the actual data items we use are less likely to have been materially affected. Nonetheless, the potential impact of this issue on our analyst coverage and statistical results is an empirical question.

Figure 1

Distribution of New Buys, Holds and Sells Between January 1997 and December 2003 by Year



recommendations made outside our sample period of January 1, 1997 to December 31, 2003, recommendations not issued by top 10 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.

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 seven 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; and Kadan et al., 2008) which were put into effect on July 9, 2002.[7]

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.

7 Refer to Barber et al. (2006) for more information about these rules.

Table 2
Transition Matrix of Recommendation Changes

	New Rating				
Old Rating	*Buy*	*Hold*	*Sell*	*Total*	*Total%*
Buy	–	6508 (46%)	278 (2%)	6786 (48%)	48%
Hold	4,739 (34%)	–	1,630 (11%)	6,369 (45%)	45%
Sell	149 (1%)	865 (6%)	–	1,014 (7%)	7%
Total Total%	4,888 (35%)	7,373 (52%)	1,908 (13%)	14,169	– 100%
		mean ratio of buys to sells = 2.6:1			

Notes:
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.

4. METHOD

This section describes how we measure the market impact of new stock recommendations, and how we content analyse analyst research reports to obtain data for our measures of overoptimism, overconfidence and representativeness biases. 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 buy and sell recommendations.

(i) 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. The relevant event date is when the stock recommendation is changed from its previous rating to new buy or sell. Performance is evaluated on stocks issued between January 1, 1997 and December 31, 2002.

(a) Return Generating Method

The reference portfolio approach, with the event firm matched on the basis of industry, size and book-to-market, is used to generate our benchmark. Intuitively, matching primarily by industry is appropriate compared with an economy-wide benchmark, because analysts often study firms within their industry context and specialise 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 and 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.

(b) 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,[8] 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.[9] Portfolios are formed in June of each year, starting in June 1997 and ending in June 2003, 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 capitalisation 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 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 firm's 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 beginning of the month following the recommendation, and ending T months later. Firm BHARs are calculated as follows:

$$\mathrm{BHAR}_{iT} = \prod_{t=1}^{T} (1 + R_{it}) - \prod_{t=1}^{T} (1 + E(R_{pt})). \tag{1}$$

Some stocks are delisted between the date of change in stock recommendation and before the end of the 12-month period. For all stocks that have missing returns after the

8 http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

9 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.

dates of their new stock recommendations, the returns on the corresponding reference portfolios are deemed to be their realised returns (Barber and Lyon, 1997).[10]

The conventional test-statistic for the test of the null hypothesis that the average BHAR for the sample firms is equal to zero may be biased because the standard errors fail to take into account that stock return volatility varies over time (Jegadeesh and Karceski, 2004). Further, Mitchell and Stafford (2000) show that even small residual cross-correlations can seriously bias the test-statistic upwards. On the other hand, Jegadeesh and Karceski (2004) acknowledge their heteroskedasticity and serial correlation consistent statistic is over conservative and particularly prone to over-rejection in the left tail of the distribution (their Table V, pp. 36–37) which applies in particular to our new sells sample. Nonetheless, we compute the Jegadeesh and Karceski (2004) standard errors even though these are likely to underestimate the true *t*-statistics.

(ii) Content Analysis Method

Data to test null hypotheses $H1_0$, $H2_0$ and $H3_0$ relating to potential analyst overoptimism, overconfidence and corporate change (activity level) biases 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*. We employ the first three measures to proxy for overoptimism (OPTIMISM), overconfidence (CERTAINTY) and representativeness (ACTIVITY) analyst cognitive biases. The use of *Diction* is well-established in the applied linguistics literature (e.g., Hart, 2000 and 2001). Its validity and reliability as a computerised content analysis program has been widely attested to (e.g., Morris 1994; and 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 analyse the numerical values in their reports, but also the textual data. They conclude that analyst reports are characterised 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 behavioural biases.

(iii) Factors Influencing Analysts' Decisions to Issue Buy and Sell Stock Recommendations and Subsequent Stock Performance

We first fit a logistic regression model to determine the factors that differentiate between new buy and new sell recommendations. We subsequently employ closely related models to explore for differences in the characteristics of successful and unsuccessful new buy and new sell analyst recommendations. In the first case, the dependent variable is RATING, and in the second SUCCESS. The independent variables in all models, defined in Section 2 above, are OPTIMISM, CERTAINTY, ACTIVITY, PRICE_MOM, FIRM_SIZE, BTOM, INVEST_RELATE1 and INVEST_RELATE2, while ANALY_FOLL

10 In order to avoid 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 of the same type that are changed within a period of six months of the first change (either by the same broker or a different broker) are dropped from our analysis.

is a control variable. For the model distinguishing between new buy and new sell analyst recommendations, binary variable RATING denotes the new buy (RATING = 1) or the new sell (RATING = 0) stock recommendation. When fitting the logit models to differentiate the characteristics of successful and unsuccessful new buy (sell) recommendations, SUCCESS = 1 if the new buy (sell) recommendation subsequently outperforms the benchmark by at least 10% (underperforms the reference portfolio benchmark by at least 10%), and = 0, otherwise (i.e., unsuccessful).

Diction variables OPTIMISM, CERTAINTY and ACTIVITY, which serve as proxies for overoptimism, overconfidence and representativeness psychological biases, are derived from the actual research reports written by analysts to justify their stock recommendations. INVEST_RELATE1 and INVEST_RELATE2, the variables measuring the relationship between brokerage houses and firms are hand collected from the same research reports that provide scores for OPTIMISM, CERTAINTY and ACTIVITY. 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:

$$\begin{aligned}\text{RATING(SUCCESS)} &= \text{LOGIT}(\pi) = \text{LN}\left(\frac{\pi}{1-\pi}\right)\\ &= \alpha + \beta_1\text{OPTIMISM}_{j,t} + \beta_2\text{CERTAINTY}_{j,t} + \beta_3\text{ACTIVITY}_{j,t}\\ &\quad + \beta_4\text{PRICE\_MOM}_{j,t-1} + \beta_5\text{FIRM\_SIZE}_{j,t-1} + \beta_6\text{BTOM}_{j,t-1}\\ &\quad + \beta_7\text{INVEST\_RELATE1}_{j,t} + \beta_8\text{INVEST\_RELATE2}_{j,t}\\ &\quad + \beta_9\text{ANALY\_FOLL}_{j,t} + \varepsilon_{j,t} \qquad (2)\end{aligned}$$

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

However, the standard errors will be biased downwards since the above logit estimation treats each observation as independent, while the data has multiple observations for the same firm. Following Shumway (2001), we divide the test statistic by the average number of observations per firm to obtain an unbiased statistic.

5. MARKET REACTION TO CHANGES IN STOCK RECOMMENDATION

This section reports the market reaction to stock recommendations that are changed to buy and sell categories over the following 12 months. Performance is observed for new buy and sell stock recommendations issued between January 1, 1997 and December 31, 2002.

(i) Performance of New Buy and New Sell Recommendations

Table 3 summarizes the abnormal return performance attributable to our new buy and sell stock recommendations. Panel A shows that after removing multiple recommendations the BHARs for the remaining 2,232[11] new buy cases are driven

11 Our sample of new buy recommendations is reduced from 4,888 to 2,232 (from 1,908 to 684 for new sells) after elimination of multiple recommendations. These arise when a change in the stock recommendation is followed by a change by another analyst and that change is in the same direction as the first analyst's change within a period of six months.

Table 3

Performance of New Buy and Sell Recommendations

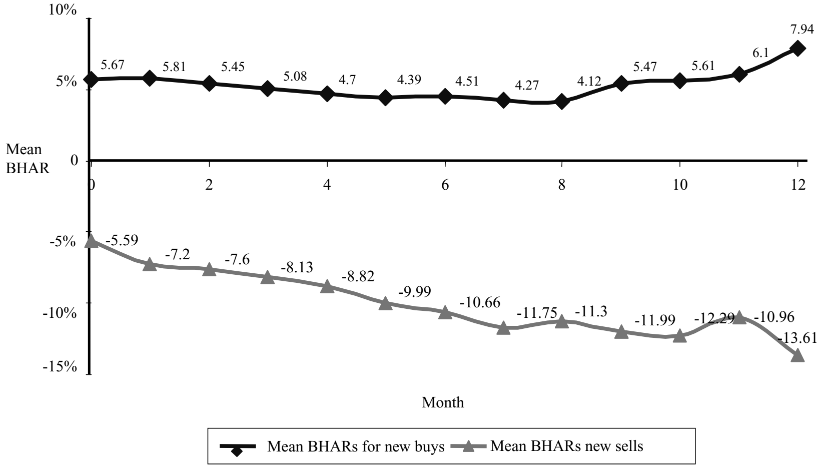
Months	*BHAR Mean (%)*	*BHAR Median (%)*	*t-statistic*	*z-statistic (Sign Test)*	*Live Firms*
Panel A: Performance of New Buy Recommendations					
0	5.67	3.53	6.14[a]	11.07[a]	2232
1	5.81	3.37	5.74[a]	7.43[a]	2225
2	5.45	2.42	3.66[a]	4.38[a]	2213
3	5.08	1.60	3.09[b]	2.43[c]	2202
4	4.70	0.68	2.48[c]	0.97	2188
5	4.39	0.42	2.10[c]	0.66	2182
6	4.51	−0.71	1.94[d]	−0.83	2174
7	4.27	−1.62	1.87[d]	−2.26[c]	2159
8	4.12	−2.98	1.66[d]	−3.70[a]	2153
9	5.47	−3.77	1.78[d]	−4.13[a]	2144
10	5.61	−5.28	1.60	−5.27[a]	2132
11	6.10	−5.39	1.57	−5.14[a]	2123
12	7.94	−4.97	1.40	−4.38[a]	2109
Panel B: Performance of New Sell Recommendations					
0	−5.59	−4.34	−4.18[a]	−7.07[a]	684
1	−7.20	−5.80	−4.30[a]	−7.99[a]	679
2	−7.60	−8.11	−2.95[b]	−7.30[a]	676
3	−8.13	−8.31	−2.01[c]	−7.38[a]	671
4	−8.82	−8.57	−1.81[d]	−7.84[a]	667
5	−9.99	−10.80	−1.67[d]	−8.45[a]	663
6	−10.66	−11.39	−1.65	−7.69[a]	658
7	−11.75	−13.16	−1.59	−7.69[a]	655
8	−11.30	−15.90	−1.61	−8.37[a]	646
9	−11.99	−16.25	−1.53	−9.06[a]	639
10	−12.29	−18.15	−1.50	−9.75[a]	634
11	−10.96	−19.60	−1.54	−9.75[a]	628
12	−13.61	−19.86	−1.39	−10.29[a]	625

Notes:
This table provides the buy-and-hold abnormal returns (BHARs) for new buy and new sell recommendations issued between January 1, 1997 and December 31, 2002. Panel A relates to new buys, and Panel B to new sells. Column 1 provides the performance period, where month 0 is the month of recommendation change, and columns 2–4 the BHAR mean, median and *t*-statistics. Column 6 provides the number of firms existing over the 12-month horizon.
[a,b,c] and [d] denote significance at 0.1%, 1%, 5% and 10% levels, respectively.

mainly by the returns in the month of recommendation change (month 0), and there is no post-recommendation drift. Thus, mean abnormal return in the month of new recommendation is +5.7% ($t = 6.1$) and does not change significantly in the subsequent months. By month 12, 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), Barber et al. (2001) and Ryan and Taffler (2006) that the value of new buy recommendations is short-lived, lasting only for one month.

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 these 684 cases is −5.6%

Figure 2
Mean BHARs for New Buy and New Sell Recommendations



($t = -4.2$), and mean BHAR increases to -13.6% ($t = -1.4$) by month 12.[12] Median BHAR is significantly negative over the 12-month period, rising from -4.3% in month 0 ($z = -7.1$) to -19.9% ($z = -10.3$) 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 behaviour over time.

The performance of new sell recommendations observed here is again consistent with the findings of Stickel (1995), Womack (1996), Barber et al. (2001) and Ryan and Taffler (2006) 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.

(ii) Do All Stocks Perform as Expected?

Table 4 provides the percentages of analyst new buy and new sell stock recommendations that perform in line with, and at variance to, analyst expectations. Panel A shows that three in five (61%) 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 (44%) still have positive BHARs, with the majority (56%) experiencing negative returns. The interesting question is what percentage of these stocks actually attains at least the minimum 10% outperformance of the industry benchmark stipulated by the brokerage firms in their definition of buy

12 However as indicated in Section 4*(i)*(b) above, the Jegadeesh and Karceski (2004) *t*-statistics that allow for heteroskedasticity may be biased downwards. The comparative unadjusted *t*-statistic is -4.7.

recommendations. Panel A also shows that, on average, only just over three out of 10 (31%) of stocks that receive new buy status outperform their respective benchmark by at least 10% over the 12-month period, the minimum outperformance required by our brokerage firms to justify a buy recommendation; whilst almost six out of ten (59%) do not.

Table 4

Performance of New Buy and Sell Recommendations Over Time

Panel A: Performance of New Buy Recommendations Over Time: $n = 2{,}232$

	No. of Firms with Positive Return (BHAR > =0)		*No. of Firms with Negative Return (BHAR < 0)*		*No. of Firms that Outperform the Benchmark by > =10%*	
Month	*n*	%	*n*	%	*n*	%
0	1,378	61.0	854	38.3	535	24.0
1	1,292	57.9	940	42.1	604	27.1
2	1,220	54.7	1,012	45.3	662	29.7
3	1,174	52.6	1,058	47.4	655	29.4
4	1,139	51.0	1,092	49.0	662	29.7
5	1,135	50.8	1,097	49.2	669	30.0
6	1,096	49.1	1,136	50.9	689	30.8
7	1,062	47.6	1,170	52.4	697	31.2
8	1,028	46.1	1,204	53.9	697	31.2
9	1,018	45.6	1,214	54.4	697	31.2
10	991	44.6	1,241	55.4	695	31.1
11	994	44.5	1,238	55.5	701	31.4
12	991	44.4	1,220	55.6	698	31.3

Panel B: Performance of New Sell Recommendations Over Time: $n = 684$

	No. of Firms with Negative Return (BHAR < 0)		*No. of Firms with Positive Return (BHAR > 0)*		*No. of Firms that Underperform the Benchmark by > =10%*	
Month	*n*	%	*n*	%	*n*	%
0	435	63.6	249	36.4	225	32.9
1	447	65.4	237	34.6	286	41.8
2	438	64.0	246	36.0	312	45.6
3	439	64.2	245	35.8	317	46.4
4	445	65.1	239	34.9	331	48.4
5	440	64.3	244	35.7	349	51.0
6	443	64.8	241	35.2	368	53.8
7	443	64.8	241	35.2	373	54.5
8	452	66.1	232	33.9	375	54.8
9	461	67.4	223	32.6	388	56.7
10	470	68.7	214	31.3	391	57.2
11	470	68.7	214	31.3	393	57.5
12	477	69.7	207	30.3	401	58.6

Notes:
This table shows how stocks with new buy/sell recommendations issued between January 1, 1997 and December 31, 2002 perform over the 12-month period subsequent to the recommendation change. Panel A relates to new buys, and Panel B to new sells. Column 1 indicates the month relative to the recommendation change (month 0). Columns 2 and 3 (4 and 5) show the number and percentage of firms with positive and negative (negative and positive) returns in Panel A (Panel B). Columns 6 and 7 of Panel A (Panel B) provide the number and percentage of buy (sell) recommendations yielding buy-and-hold abnormal returns (BHARs) of at least 10% (−10%) as per brokerage firms' definition of successful recommendations.

In the case of new sell recommendations, Table 4, Panel B indicates that in the month of the recommendation change, although three in five of the stocks in our sample receiving sell ratings (64%) earn negative abnormal returns, over a third (36%) 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 ten (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.

In summary, the descriptive statistics of Table 4 demonstrate how new sell recommendations perform far more in line with analyst expectations than their new buy counterparts 12 months after the recommendation change.

6. RESULTS

This section reports our empirical results which test for the existence of both cognitive bias and conflicts of interest in analyst stock ratings. First we describe the differences in apparent drivers for analyst new buy and new sell recommendations. We then explore further for evidence of analyst cognitive bias and conflicts of interest by comparing the characteristics of 'successful' and 'unsuccessful' new buy recommendations, i.e., those which meet their industry relative target benchmark (outperform the benchmark by at least 10%) over the next 12 months, and those that do not. We also repeat the exercise for new sell recommendations ('success' denoted by underperforming the benchmark by at least 10%).

Of the 2,232 new buy stocks excluding multiple observations, 875 of these stocks have accompanying research reports available on the Thompson Financial *Investext Plus* database, although seven cases are removed as outliers, leaving 868 cases with full data for processing. Of the equivalent 684 new sell stocks, 180 have accompanying research reports available, and after 14 are removed as extreme cases, 166 are used in our analysis. All analyst reports are spread throughout the sample period.

(i) Differences in the Characteristics of New Buy and New Sell Analyst Recommendations

(a) Univariate Analysis

Table 5 provides statistics for the main variables used in this analysis relating to our 868 new buy recommendations, and our 166 new sell recommendations with analyst reports available. Results show that firms that are awarded new buy recommendations have larger market capitalisation (mean (median) FIRM_SIZE = \$11.3 (2.3) billion) compared to their new sell counterparts (mean (median) FIRM_SIZE = \$5.3 (2.2) billion), with the mean difference significant at the 0.1% level (median difference is not significant). New buy stocks have generally performed well in the recent past with prior 12-month (mean (median) monthly return (PRICE_MOM) of 1.22% (1.24%)) compared with new sells, when mean (median) PRICE_MOM = −0.85% (−0.23%), with difference of 2.07% (1.47%) significant at the 0.1% (0.1%) level. New buy stocks have lower book-to-market ratios (mean (median) BTOM = 0.43 (0.30)) and, as such, may be classified as more like glamour stocks, whereas new sell stock recommendations have higher book-to-market ratios (mean (median) BTOM = 0.71 (0.46)), and may be classified as more like value stocks. The difference in means (medians) is again

Table 5

Characteristics of New Buy and New Sell Recommendations

	New Buy Recommendations			*New Sell Recommendations*						
	n = 868			*n = 166*						
Variables	*Mean*	*Median*	*Std. Dev.*	*Mean*	*Median*	*Std. Dev.*	*Difference in Means*	*t- statistic*[1]	*Difference in Medians*	*z-statistic*[2]
OPTIMISM	51.49	51.45	2.57	50.33	50.07	2.59	1.17	5.35[a]	1.39	5.91[a]
CERTAINTY	50.65	50.69	2.26	50.43	50.52	2.03	0.22	1.18	0.16	1.00
ACTIVITY	47.86	48.77	5.24	48.03	48.57	4.35	−0.17	−0.39	0.20	0.48
PRICE_MOM (%)	1.22	1.24	4.64	−0.85	−0.23	4.93	2.07	5.22[a]	1.47	5.24[a]
FIRM_SIZE (RAW) ($bn)	11.29	2.32	30.87	5.27	2.16	9.97	6.02	4.62[a]	1.63	1.16
FIRM_SIZE (LN) ($m)	7.87	7.75	1.62	7.62	7.68	1.47	0.25	1.88[d]	0.07	1.16
BTOM	0.43	0.30	0.50	0.71	0.46	1.05	−0.28	−3.31[a]	−0.17	5.52[a]
INVEST_RELATE1	0.47	0.00	0.50	0.30	0.00	0.46	0.17	4.42[a]	0.00	4.13[b]
INVEST_RELATE2	0.17	0.00	0.38	0.11	0.00	0.31	0.06	2.27[c]	0.00	2.00[c]
ANALY_FOLL	30.82	28.00	15.19	27.70	27.00	12.64	3.12	2.82[b]	1.00	1.78[d]

Table 5 (Continued)

Variable Definitions		
$\text{OPTIMISM}_{j,t}$	=	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 overoptimism;
$\text{CERTAINTY}_{j,t}$	=	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;
$\text{ACTIVITY}_{j,t}$	=	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;
$\text{PRICE\_MOM}_{j,t-1}$	=	firm *j*'s percentage change in stock return over the year to the end of the calendar month immediately prior to the recommendation change expressed on an average monthly basis;
$\text{FIRM\_SIZE (RAW)}_{j,t-1}$	=	firm size in billion dollars, measured as the market value of equity for firm *j* at the end of the year preceding the change of recommendation;
$\text{FIRM\_SIZE (LN)}_{j,t-1}$	=	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;
$\text{BTOM}_{j,t-1}$	=	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;
$\text{INVEST\_RELATE1}_{j,t}$	=	a variable that takes a value of 1 if the brokerage house is the underwriter *or* discloses current holdings in the firm being researched, and 0 otherwise;
$\text{INVEST\_RELATE2}_{i,t}$	=	a variable that takes the value 1 if the brokerage firm is *both* an underwriter *and* has current holdings in the firm being researched, and 0 otherwise;
$\text{ANALY\_FOLL}_{j,t}$	=	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.

Notes:
The table provides statistics on the characteristics of new buy (sell) recommendations that are issued between January 1, 1997 and December 31, 2002 with analyst reports available. Column 1 shows the variables, and columns 2–4 (5–7) mean, median, and standard deviation for the new buy (sell) firms, and columns 8–11 the differences in the sample means, and medians with associated *t*- and *z*-statistics.

[a,b,c,d] denote significance at the 0.1%, 1%, 5% and 10% levels respectively.

[1]Independent sample *t*-test.

[2]Wilcoxon-Mann-Whitney non-parametric test.

significant at the 0.1% (0.1%) level. Mean (median) of the number of analysts following new buy stocks (ANALY_FOLL) = 30.8 (28), and differs significantly to the mean (median) number following new sell stocks = 27.7 (27) at the 1% (10%) level.

As expected, the language used by investment analysts to justify their research reports is more optimistic (OPTIMISM) for new buys than in the case of new sells (significant at the 0.1% level for both mean and median differences). However, there is no significant difference in the language indicating CERTAINTY, and ACTIVITY between new buy and new sell analyst reports. As regards corporate relationships, the proportion of new buys with either an investment banking or a direct investment relationship with the firm being reported on (INVEST_RELATE1) is higher for new buys than it is for new sells (0.47 compared to 0.30, and significant at the 1% level), and similarly with the equivalent proportions for the joint relationship variable INVEST_RELATE2 (0.17 compared with 0.11, significant at the 5% level).

(b) Logistic Regression Model Results

Table 6 reports the results from running the logistic regression model of equation (2) to distinguish between new analyst buy and sell recommendations. Whereas the

Table 6

Factors Influencing New Buy and New Sell Recommendations

Variable	*Expected Sign*	*Coefficient*	*Wald Statistic*	*p-value*
OPTIMISM	+	0.154	12.44	0.000[a]
CERTAINTY	+	−0.003	0.19	0.664
ACTIVITY	+	−0.034	1.75	0.185
PRICE_MOM	+	0.092	15.47	0.000[a]
FIRM_SIZE (LN)	+	−0.027	0.16	0.688
BTOM	−	−0.403	3.83	0.050[c]
INVEST_RELATE1	+	0.768	17.29	0.000[a]
INVEST_RELATE2	+	1.005	8.58	0.003[b]
ANALY_FOLL	+	0.015	1.54	0.215
INTERCEPT	?	−5.060	3.72	0.054[d]
likelihood ratio-model χ^2		98.39		
χ^2 significance (*p*-value)		0.000[a]		

Notes:
This table reports the factors that differentiate between 868 new buy recommendations, and 166 new sell recommendations made by the top 10 brokerage firms between January 1, 1997 and December 31, 2002 with full analyst research reports available. The following logistic regression model is run where RATING = 1 if a new buy recommendation, and 0 if new sell. Refer to Table 5 for description of the independent variables.
[a,b,c,d] indicate significance at the 0.1%, 1%, 5% and 10% levels respectively. The Wald statistic is adjusted for the fact that there are several observations from the same firm by dividing by 1.49, the average number of observations per firm.
Our logistic model is specified in equation (2) as follows:

$$\begin{aligned}\text{RATING} = \text{LOGIT}(\pi) = \text{LN}\left(\frac{\pi}{1-\pi}\right)\\ = \alpha + \beta_1\text{OPTIMISM}_{j,t} + \beta_2\text{CERTAINTY}_{j,t} + \beta_3\text{ACTIVITY}_{j,t}\\ + \beta_4\text{PRICE\_MOM}_{j,t-1} + \beta_5\text{FIRM\_SIZE}_{j,t-1} + \beta_6\text{BTOM}_{j,t-1}\\ + \beta_7\text{INVEST\_RELATE1}_{j,t} + \beta_8\text{INVEST\_RELATE2}_{j,t}\\ + \beta_9\text{ANALY\_FOLL}_{j,t} + \varepsilon_{j,t}\end{aligned}$$

OPTIMISM parameter is positive and very highly significant (at the 0.1% level) with the expected sign, the CERTAINTY measure, proxying for overconfidence, does not differ between buys and sells. Given the fact that analysts appear to get the majority of their new buy recommendations (as opposed to new sells) wrong, we may interpret this result as consistent with analyst overoptimism leading to an increased probability of a buy recommendation. As such we have evidence to reject null hypothesis $H1_{0.}$

Among the four variables proxying for representativeness, PRICE_MOM and BTOM have significant parameter estimates, while ACTIVITY and FIRM_SIZE are insignificant. PRICE_MOM is significant at the 0.1% level while BTOM is significant at the 5% level, both in the expected direction. We thus have no evidence that analysts associate changes within the firm (such as employment of new management) with good future stock performance *contra* Fogarty and Rogers (2005). Nor is firm size a distinguishing characteristic between analyst new buy and sell stock recommendations. On the other hand, the likelihood of a buy recommendation is much higher for stocks that have performed well in the past, consistent with analysts preferring stocks with good prior performance (Stickel, 2000; and Jegadeesh et al., 2004). Further, the evidence suggests that analysts are more likely to associate growth or glamour stocks with good future performance, and therefore award buy recommendations to them. Overall, our results are consistent with analysts also suffering from representativeness cognitive bias in their stock recommendations, at least in the case of new buys. Although we cannot reject null hypotheses $H3_0$ and $H5_0$, on this basis, we do have evidence that allows us to reject $H4_0$ and $H6_0$ at conventional levels.

Corporate relationship variables INVEST_RELATE1 and INVEST_RELATE2 are included to test for whether the closeness of the relationship between the investment bank and the firm being analysed has any bearing on the type of recommendation issued by sell-side analysts. INVEST_RELATE1 = 1 if the brokerage house is either an underwriter of the firm *or* has a current holding in the firm, and = 0 otherwise. In parallel, INVEST_RELATE2 = 1 if the brokerage house is *both* an underwriter and has current investments in the firm, and = 0 otherwise. Both measures have positive and significant (at the 1% level) parameter estimates. Our results demonstrate that where there is a potential conflicts of interest relationship between the investment bank and the firm being reported on, the probability of a buy recommendation is greatly increased. This result is consistent with other studies in the literature (e.g., Michaely and Womack, 1999). We thus reject null hypothesis $H7_0$ that the corporate relationship between the investment bank and the particular firm does not influence the type of recommendation that the analyst issues.

The control variable, ANALY_FOLL, is not significant though its sign is in the expected direction. On this basis, we find no evidence that better followed stocks are likely to be associated with a greater probability of a buy recommendation.[13]

(ii) Successful vs. Unsuccessful Stock Recommendations

In Section 5 above, we show that a large percentage of stocks with new buy recommendations subsequently underperform their respective benchmark, while a

13 Including a dummy variable in our logistic model to control for bull (i.e., prior to 2000) and bear (i.e., 2000 onwards) market conditions does not affect our conclusions save that BTOM is no longer significant. Although analysts, not surprisingly, have a greater propensity to issue buys prior to 2000, they seem equally prone to the effects of cognitive bias and conflicts of interest independent of market conditions.

much smaller percentage of new sell recommendations are unsuccessful. In this subsection, we seek to establish whether analyst cognitive biases (overoptimism, overconfidence and representativeness) and conflicts of interest might help explain analyst recommendation errors. In particular, are there differences in the characteristics of stocks recommended as buys that analysts get right and those they get wrong, and similarly with new sells? New buy (sell) recommendations are regarded successful if they outperform the reference portfolio benchmark by at least 10% (underperform the reference portfolio benchmark by at least 10%) after 12 months, and unsuccessful otherwise.

(a) Univariate Analysis

Table 7 compares the characteristics of successful new buy recommendations with unsuccessful ones in Panel A, and the equivalent for successful and unsuccessful new sell recommendations in Panel B.

Panel A of Table 7 shows that successful new buy recommendations tend to have smaller market capitalisation (mean (median) FIRM_SIZE = \$9.3 (2.0) billion) compared to their unsuccessful buy counterparts (mean (median) FIRM_SIZE = \$12.6 (2.7) billion) with the mean (median) difference almost significant at the 10% (significant at 1%) level. Successful new buys have not performed as well in the recent past, with prior 12-month mean (median) monthly return (PRICE_MOM) of 0.55% (0.85%) compared with unsuccessful new buys, when mean (median) PRICE_MOM = 1.63% (1.52%), with difference of 1.09% (0.67%), significant at the 0.1% (1%) level. Successful new buy recommendations have relatively higher book-to-market ratios (mean (median) BTOM = 0.50 (0.33)) and, as such, resemble more value stocks, whereas unsuccessful new buy recommendations have lower book-to-market ratios (mean (median) BTOM = 0.39 (0.28)), and look more like growth stocks. The difference in means (medians) is again significant at the 1% (1%) level. Mean (median) INVEST_RELATE1 is higher for successful new buys than for unsuccessful new buys, with difference significant at the 5% (5%) level. Conversely, mean (median) INVEST_RELATE2 is higher when analyst recommendations are unsuccessful than when they are successful, with difference significant at the 0.1% (0.1%) level. The analyst control variable, ANALY_FOLL, does not differ between successful and unsuccessful new buys.

Panel B shows successful new sell recommendations have larger market capitalisation (mean (median) FIRM_SIZE = \$10.7 (4.4) billion) compared to their unsuccessful new sell counterparts (mean (median) FIRM_SIZE = \$3.9 (1.7) billion) with the difference significant at the 5% (1%) level. However, successful and unsuccessful new sell recommendations do not differ along any other dimension.

(b) Logistic Regression Model Results

The logistic regression model of equation (2) is also separately fitted for our 868 new buy cases, and our 166 new sells. However, the dependent variable now denotes successful or unsuccessful new buy (sell) recommendations. In the new buy logistic model, SUCCESS = 1 if the stock outperforms the benchmark by at least 10% after 12 months, and = 0 otherwise. In the case of new sells, SUCCESS = 1 if the stock underperforms the benchmark by at least 10% after 12 months, and 0 otherwise.

Of the 868 new buys, only 332 (38%) meet the recommendation target of at least 10% outperformance. Table 8 reports the results of running the logistic regression

Table 7

Characteristics of Successful and Unsuccessful New Buy and New Sell Recommendations

Panel A: New Buy Recommendations

	Successful Recommendations			*Unsuccessful Recommendations*						
	n = 332			*n = 536*						
Vsariable	*Mean*	*Median*	*St. Dev.*	*Mean*	*Median*	*St. Dev.*	*Difference in Means*	*t-Statistic* [1]	*Difference in Medians*	*z-Statistic* [2]
OPTIMISM	51.53	51.55	2.77	51.47	51.39	2.44	0.06	0.35	0.16	0.32
CERTAINTY	50.62	50.70	2.47	50.67	50.68	2.12	−0.04	0.27	0.02	0.01
ACTIVITY	47.83	48.64	4.81	47.88	48.82	5.49	−0.06	0.15	−0.18	1.36
PRICE_MOM (%)	0.55	0.85	4.79	1.63	1.52	4.50	−1.09	3.37[a]	−0.67	2.83[b]
FIRM_SIZE (RAW) ($bn)	9.25	1.98	30.11	12.55	2.67	31.30	−3.30	1.55	−0.69	3.10[b]
FIRM_SIZE (LN) ($m)	7.65	7.59	1.57	8.01	7.89	1.65	−0.35	3.12[b]	−0.30	3.10[b]
BTOM	0.50	0.33	0.60	0.39	0.28	0.43	0.11	2.88[b]	0.05	2.86[b]
INVEST_RELATE1	0.51	1.00	0.50	0.44	0.00	0.50	0.07	2.00[c]	1.00	2.00[c]
INVEST_RELATE2	0.11	0.00	0.32	0.21	0.00	0.41	−0.10	3.88[a]	0.00	3.64[a]
ANALY_FOLL	31.51	29.00	15.91	30.40	28.00	14.72	1.11	1.05	1.00	0.72

Table 7 (Continued)

Panel B: New Sell Recommendations

	Successful Recommendations			*Unsuccessful Recommendations*						
	n = 33			*n* = 133						
Variable	*Mean*	*Median*	*St. Dev.*	*Mean*	*Median*	*St. Dev.*	*Difference in Means*	*t-Statistic*	*Difference in Medians*	*z-Statistic*
OPTIMISM	50.04	50.14	2.77	50.40	50.01	2.55	−0.35	0.70	0.13	0.04
CERTAINTY	50.00	50.49	2.12	50.53	50.55	2.00	−0.53	1.35	−0.06	1.07
ACTIVITY	48.15	48.88	4.78	48.00	48.55	4.25	0.15	0.18	0.33	0.67
PRICE_MOM (%)	−1.07	−0.47	2.93	−0.80	−0.15	5.32	−0.27	0.39	−0.33	0.80
FIRM_SIZE (RAW) ($bn)	10.66	4.39	17.97	3.94	1.68	6.08	6.72	2.12[c]	2.70	2.85[b]
FIRM_SIZE (LN) ($m)	8.32	8.39	1.47	7.44	7.43	1.42	0.88	3.18[b]	0.96	2.85[b]
BTOM	0.59	0.36	0.96	0.73	0.48	1.08	−0.14	0.68	−0.12	1.72[d]
INVEST_RELATE1	0.30	0.00	0.47	0.29	0.00	0.46	0.01	0.11	0.00	0.11
INVEST_RELATE2	0.12	0.00	0.33	0.11	0.00	0.31	0.01	0.26	0.00	0.26
ANALY_FOLL	30.27	31.00	12.98	27.06	26.00	12.53	3.21	1.31	5.00	1.28

Notes:
This table provides statistics on the characteristics of successful and unsuccessful new buy (sell) recommendations that are issued between January 1, 1997 and December 31, 2002 with full analyst reports available. A new buy (sell) recommendation is defined as successful if it outperforms (underperforms) the benchmark by > = 10%. Panel A relates to new buys, and Panel B to new sells. Column 1 shows the variables, and columns 2–4 (5–7) mean, median, and standard deviation for the successful (unsuccessful) stock recommendations, and columns 8–11 show the differences in the sample means and medians with *t*- and *z*-statistics. Refer to Table 5 for descriptions of the independent variables.

[a,b,c,d] denote significance at 0.1%, 1%, 5% and 10% levels respectively.

[1]Independent sample *t*-test.

[2]Wilcoxon-Mann-Whitney non-parametric test.

Table 8

Factors Differentiating Between Successful and Unsuccessful New Buy Recommendations

Variable	*Coefficient*	*Wald Statistic*	*p-value*
OPTIMISM	0.017	0.25	0.620
CERTAINTY	−0.013	0.11	0.737
ACTIVITY	0.009	0.25	0.615
PRICE_MOM	−0.060	9.67	0.002[b]
FIRM_SIZE (LN)	−0.308	15.51	0.000[a]
BTOM	0.388	4.13	0.042[c]
INVEST_RELATE1	0.120	0.40	0.526
INVEST_RELATE2	−0.700	6.53	0.011[c]
ANALY_FOLL	0.032	16.01	0.000[a]
INTERCEPT	0.259	0.01	0.906
likelihood ratio-model χ^2	64.33		
χ^2 significance (*p*-value)	0.000[a]		

Notes:
This table reports the factors that differentiate between 332 successful and 536 unsuccessful new buy recommendations issued by the top 10 brokerage houses between January 1, 1997 and December 31, 2002 with full analyst research reports available. A new buy stock recommendation is defined as successful if it outperforms the benchmark by > = 10%, and unsuccessful otherwise. The following logistic regression model is run where SUCCESS = 1 if a successful new buy recommendation is issued, and 0 if an unsuccessful buy is issued. Refer to Table 5 for description of the independent variables.
[a,b,c,d] indicate significance at the 0.1%, 1%, 5% and 10% levels respectively.
The Wald statistic is adjusted for the fact that there are several observations from the same firm by dividing by 1.42, the average number of observations per firm.
Our logistic model is specified in equation (2) as follows:

$$\begin{aligned}\text{RATING} &= \text{LOGIT}(\pi) = \text{LN}\left(\frac{\pi}{1-\pi}\right)\\ &= \alpha + \beta_1\text{OPTIMISM}_{j,t} + \beta_2\text{CERTAINTY}_{j,t} + \beta_3\text{ACTIVITY}_{j,t}\\ &\quad + \beta_4\text{PRICE\_MOM}_{j,t-1} + \beta_5\text{FIRM\_SIZE}_{j,t-1} + \beta_6\text{BTOM}_{j,t-1}\\ &\quad + \beta_7\text{INVEST\_RELATE1}_{j,t} + \beta_8\text{INVEST\_RELATE2}_{j,t}\\ &\quad + \beta_9\text{ANALY\_FOLL}_{j,t} + \varepsilon_{j,t}\end{aligned}$$

analysis to distinguish between successful and unsuccessful new buy stock recommendations. The results show that overoptimism and overconfidence as measured by OPTIMISM and CERTAINTY respectively appear to have no role in differentiating between buys that perform as expected and those performing contrary to expectation. However, we have clear evidence that analysts seem to be suffering from representativeness bias with the new buy stocks that they get wrong having much higher prior returns (PRICE_MOM), significant at the 1% level, are more likely to be growth stocks (BTOM), significant at the 5% level, and be much larger (FIRM_SIZE), significant at 0.1% level. Such stocks are also likely to be more widely followed (ANALY_FOLL), again significant at the 0.1% level. The change narrative variable (ACTIVITY) is not significant.

In addition, although dummy variable INVEST_RELATE1 is not significant, INVEST_RELATE2 is, at the 5% level. There is thus clear evidence that unsuccessful buy recommendations are likely to be associated more with strong corporate relationships with the sell-side house, i.e., when there is both a corporate finance relationship, and the house holds stock in the firm.

Table 9

Determinants of Successful and Unsuccessful New Sell Recommendations

Variable	*Coefficient*	*Wald Statistic*	*p-value*
OPTIMISM	−0.051	0.35	0.551
CERTAINTY	−0.187	2.93	0.087
ACTIVITY	0.025	0.20	0.658
PRICE_MOM	−0.028	0.32	0.573
FIRM_SIZE (LN)	0.708	8.73	0.003[b]
BTOM	0.230	0.78	0.376
INVEST_RELATE1	−0.272	0.29	0.591
INVEST_RELATE2	−0.180	0.07	0.798
ANALY_FOLL	−0.022	0.79	0.373
INTERCEPT	4.156	0.35	0.557
likelihood ratio-model χ^2	16.15		
χ^2 significance (p-value)	0.064[d]		

Notes:

This table reports the factors that differentiate between 33 successful and 133 unsuccessful new sell recommendations issued by the top 10 brokerage firms between January 1, 1997 and December 31, 2002 with full analyst research reports available. A new sell stock recommendation is defined as successful if it underperforms the benchmark by > = 10%, and unsuccessful otherwise. The following logistic regression model is run where SUCCESS = 1 if a successful new sell recommendation is issued, and 0 if an unsuccessful sell is issued. Refer to Table 5 for description of the independent variables.

[a,b,c,d] indicate significance at the 0.1%, 1%, 5% and 10% levels respectively.

The Wald statistic is adjusted for the fact that there are several observations from the same firm by dividing by 1.07, the average number of observations per firm.

Our logistic model is specified in equation (2) as follows:

$$\begin{aligned}\text{RATING} = \text{LOGIT}(\pi) &= \text{LN}\left(\frac{\pi}{1-\pi}\right)\\ &= \alpha + \beta_1\text{OPTIMISM}_{j,t} + \beta_2\text{CERTAINTY}_{j,t} + \beta_3\text{ACTIVITY}_{j,t}\\ &\quad + \beta_4\text{PRICE\_MOM}_{j,t-1} + \beta_5\text{FIRM\_SIZE}_{j,t-1} + \beta_6\text{BTOM}_{j,t-1}\\ &\quad + \beta_7\text{INVEST\_RELATE1}_{j,t} + \beta_8\text{INVEST\_RELATE2}_{j,t}\\ &\quad + \beta_9\text{ANALY\_FOLL}_{j,t} + \varepsilon_{j,t}.\end{aligned}$$

Our evidence does not allow us to reject null hypothesis $H3_0$ relating to the impact of firm activity levels on analyst stock recommendations. However, our results do allow us to reject null hypotheses $H4_0$ (no price momentum bias), $H5_0$ (no firm size bias), $H6_0$ (no book-to-market bias), and $H7_0$ (no impact of corporate relationships) at conventional levels. On this basis, we have additional evidence that analyst cognitive bias (specifically, representativeness bias) and potential conflicts of interest are jointly associated with an increased likelihood of underperformance in the case of new buys.

Of the 166 new sell recommendations in our sample, 33 (20%) are successful (i.e., underperform the benchmark by at least 10%). Table 9 provides parallel results to Table 8 for the logistic regression differentiating between successful and unsuccessful new sell recommendations. As can be seen, however, the only significant variable is FIRM_SIZE (at the 1% level). Successful new sell recommendations are larger than unsuccessful ones. There is no evidence of strength of analyst following (ANALY_FOLL) bearing any relationship with whether the new sell stock recommendation is successful or not, nor is there any evidence of conflicts of interest. Our results suggest that analysts making new sell recommendations are not prone to cognitive bias, at least in the way we measure these behavioural characteristics, nor are investment banking relationships a significant factor.[14, 15]

(c) Disentangling Analysts' Cognitive Biases and Conflicts of Interest[16]

Our results so far assume analyst cognitive bias and conflicts of interest are independent factors. However, strictly speaking, our tests do not allow us to disentangle their separate impacts on analyst stock recommendations.

To explore whether the effect of behavioural bias on analyst stock recommendations is indeed independent of conflicts of interest, or whether the impact of cognitive biases is exacerbated by conflicts of interest, we rerun the RATING formulation of the logistic regression model of equation (2) introducing interaction terms between the two sets of proxies. However, to avoid multicollinearity problems, we restrict our analysis to the cognitive bias variables found to be significant in Table 6 (OPTIMISM, PRICE_MOM and BTOM) and their interaction with the two conflict of interest variables (INVEST_RELATE1 and INVEST_RELATE2). Our resulting logistic model is thus given by:

$$\begin{aligned}
\text{RATING} &= \text{LOGIT}(\pi) = \text{LN}\left(\frac{\pi}{1-\pi}\right) \\
&= \alpha + \beta_1\text{OPTIMISM}_{j,t} + \beta_2\text{PRICE_MOM}_{j,t-1} + \beta_3\text{BTOM}_{j,t-1} \\
&\quad + \beta_4\text{OPTIMISM}_{j,t} * \text{INVEST_RELATE1}_{j,t} \\
&\quad + \beta_5\text{PRICE_MOM}_{j,t-1} * \text{INVEST_RELATE1}_{j,t} \\
&\quad + \beta_6\text{BTOM}_{j,t-1} * \text{INVEST_RELATE1}_{j,t} + \beta_7\text{OPTIMISM}_{j,t} \\
&\quad * \text{INVEST_RELATE2}_{j,t} + \beta_8\text{PRICE_MOM}_{j,t-1} * \text{INVEST_RELATE2}_{j,t} \\
&\quad + \beta_9\text{BTOM}_{j,t-1} * \text{INVEST_RELATE2}_{j,t} + \beta_{10}\text{ANALY_FOLL}_{j,t} + \varepsilon_{j,t}. \qquad (3)
\end{aligned}$$

Results presented in Table 10 show that whereas book-to-market, proxying for representativeness bias, is no longer significant in distinguishing between new buys and new sells, buy recommendations, as in Table 6, are again associated with greater optimism (significant at the 1% level) and higher prior-year returns which proxy for representativeness bias (significant at the 5% level). However, there is now significant interaction between optimism and both conflicts of interest variables (at the 0.1% level if the brokerage house has either a corporate finance relationship or an investment holding in the firm and at the 5% level if both). We thus have evidence that although prone to cognitive bias even when conflicts of interest are absent, where these do

14 The number of successful new sell recommendations with analyst reports available is disproportionately small and thus our results need to be treated with some circumspection. This may be due to analysts being reluctant to spell out their concerns directly when most acute. Nonetheless, when we run the equivalent logit model across the full set of 684 new sell cases with non-analyst report derived variables we find identical results to those reported in Table 9 suggesting our reported results are not biased.

15 Introducing a dummy variable in our logistic model to control for market conditions, as described in footnote 13, has no impact on our reported results whatsoever, and it, itself, is insignificant.

16 We are indebted to Danielle Lyssimachou for this suggestion which significantly strengthens the paper.

Table 10

Factors Influencing New Buy and New Sell Recommendations

Variable	*Coefficient*	*Wald Statistic*	*p-value*
OPTIMISM	0.137	10.48	0.001[b]
PRICE_MOM	0.079	4.94	0.026[c]
BTOM	−0.167	0.89	0.345
OPTIMISM * INVEST_RELATE1	0.028	17.16	0.000[a]
PRICE_MOM * INVEST_RELATE1	0.037	0.47	0.493
BTOM * INVEST_RELATE1	−0.680	2.44	0.118
OPTIMISM * INVEST_RELATE2	0.021	5.88	0.015[c]
PRICE_MOM * INVEST_RELATE2	−0.011	0.03	0.874
BTOM * INVEST_RELATE2	−0.123	0.06	0.799
ANALY_FOLL	0.010	1.52	0.218
INTERCEPT	−6.079	7.88	0.005[b]
likelihood ratio-model χ^2	101.60		
χ^2 significance (p-value)	0.000[a]		

Notes:

This table reports the factors that differentiate between 868 new buy recommendations, and 166 new sell recommendations made by the top 10 brokerage firms between January 1, 1997 and December 31, 2002 with full analyst research reports available taking into account potential interactions between cognitive bias and conflicts of interest variables. The following logistic regression model is run where RATING = 1 if a new buy recommendation, and 0 if new sell. Refer to Table 5 for description of the independent variables.

[a,b,c,d] indicate significance at the 0.1%, 1%, 5% and 10% levels respectively.

The Wald statistic is adjusted for the fact that there are several observations from the same firm by dividing by 1.49, the average number of observations per firm.

Our logistic model is specified in equation (3) as follows:

$$\begin{aligned}
\text{RATING} = \text{LOGIT}(\pi) = \text{LN}\left(\frac{\pi}{1-\pi}\right)
&= \alpha + \beta_1\text{OPTIMISM}_{j,t} + \beta_2\text{PRICE_MOM}_{j,t-1} + \beta_3\text{BTOM}_{j,t-1} \\
&\quad + \beta_4\text{OPTIMISM}_{j,t} * \text{INVEST_RELATE1}_{j,t} \\
&\quad + \beta_5\text{PRICE_MOM}_{j,t-1} * \text{INVEST_RELATE1}_{j,t} \\
&\quad + \beta_6\text{BTOM}_{j,t-1} * \text{INVEST_RELATE1}_{j,t} + \beta_7\text{OPTIMISM}_{j,t} \\
&\quad * \text{INVEST_RELATE2}_{j,t} + \beta_8\text{PRICE_MOM}_{j,t-1} * \text{INVEST_RELATE2}_{j,t} \\
&\quad + \beta_9\text{BTOM}_{j,t-1} * \text{INVEST_RELATE2}_{j,t} + \beta_{10}\text{ANALY_FOLL}_{j,t} + \varepsilon_{j,t}.
\end{aligned}$$

exist, brokerage house analysts manifest increased levels of optimism in their stock recommendations.[17]

However, an additional test of whether analyst cognitive bias and potential conflicts of interest are independent factors is to compare successful new buy recommendations with unsuccessful ones.[18] To do this we rerun the SUCCESS formulation of logistic regression model of equation (2) using the cognitive bias variables found significant in Table 8 (PRICE_MOM, FIRM_SIZE and BTOM) and their interaction terms

17 Nonetheless, strictly speaking, presence of such investment banking relationships may also justify the greater optimism manifested in the case of buy recommendations if the analyst consequently has access to better information. However, the results reported in Section 6(*ii*) above suggest this is not a very likely scenario.

18 Given the lack of any meaningful results for new sells and the small sample size, there is no point conducting any parallel analysis in this case.

with conflict of interest variables (INVEST_RELATE1, and INVEST_RELATE2) as equation (4):

$$\begin{aligned}
\text{SUCCESS} = \text{LOGIT}(\pi) = \text{LN}\left(\frac{\pi}{1-\pi}\right) \\
&= \alpha + \beta_1 \text{PRICE_MOM}_{j,t-1} + \beta_2 \text{FIRM_SIZE}_{j,t-1} + \beta_3 \text{BTOM}_{j,t-1} \\
&\quad + \beta_4 \text{PRICE_MOM}_{j,t-1} * \text{INVEST_RELATE1}_{j,t} \\
&\quad + \beta_5 \text{FIRM_SIZE}_{j,t-1} * \text{INVEST_RELATE1}_{j,t} \\
&\quad + \beta_6 \text{BTOM}_{j,t-1} * \text{INVEST_RELATE1}_{j,t} \\
&\quad + \beta_7 \text{PRICE_MOM}_{j,,t-1} * \text{INVEST_RELATE2}_{j,t} \\
&\quad + \beta_8 \text{FIRM_SIZE}_{j,t-1} * \text{INVEST_RELATE2}_{j,t} + \beta_9 \text{BTOM}_{j,t-1} \\
&\quad * \text{INVEST_RELATE2}_{j,t} + \beta_{10} \text{ANALY_FOLL}_{j,t} + \varepsilon_{j,t}.
\end{aligned} \tag{4}$$

In this case, as Table 11 shows, although all three cognitive variables proxying for representativeness bias remain significant, only FIRM_SIZE has a significant, at the 10% level, interaction with conflicts of interest variable INVEST_RELATE2. That is, there is weak evidence that a biased unsuccessful new buy recommendation is more likely in the case of larger firms where the brokerage house faces more acute conflicts of interest.

We thus conclude that although analyst cognitive bias may be related to their conflicts of interest to a lesser or greater extent, nonetheless, importantly, in the absence of conflicts of interest analysts will still manifest strong judgemental bias in their stock recommendations. This indicates that although recent regulations to address problems associated with conflicts of interests in analyst and brokerage house activity may well have had some success (e.g., Kadan et al., 2009), nonetheless, these may at best only have a limited impact on improving the quality of analyst stock recommendations. This is because analysts will continue to suffer from built in behavioural bias which is independent of conflicts of interest issues.

7. CONCLUSIONS

Using large sample data for analyst stock recommendations made by the top 10 US sell-side houses between 1997 and 2002 this study first evaluates the performance of their new buy and new sell stock recommendations over the 12 months subsequent to recommendation change. Consistent with prior research 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 for up to a year to new sell recommendations. We also find a large proportion of, in particular, new buy recommendations not performing in line with analyst expectations.

We investigate factors that might be driving analysts' new buy and new sell recommendations, as well as their judgment calls that turn out subsequently to be wrong. Our logistic regression results show that the probability that analysts will issue a buy recommendation increases with degree of analyst optimism (a proxy for overoptimism bias) even though they get the majority of their new buy recommendations wrong. Such optimism bias can have both cognitive and economic incentive explanations. These latter include enhanced access to management, 'trade-boosting', career progression

Table 11

Factors Differentiating Between Successful and Unsuccessful New Buy Recommendations

Variable	*Coefficient*	*Wald Statistic*	*p-value*
PRICE_MOM	−0.068	3.69	0.055[d]
FIRM_SIZE (LN)	−0.310	14.37	0.000[a]
BTOM	0.493	3.68	0.055[d]
PRICE_MOM * INVEST_RELATE1	0.025	0.32	0.569
FIRM_SIZE * INVEST_RELATE1	0.024	0.59	0.444
BTOM * INVEST_RELATE1	−0.152	0.13	0.717
PRICE_MOM * INVEST_RELATE2	−0.016	0.08	0.771
FIRM_SIZE * INVEST_RELATE2	−0.071	3.04	0.081[d]
BTOM * INVEST_RELATE2	−0.327	0.62	0.432
ANALY_FOLL	0.032	16.03	0.000[a]
INTERCEPT	0.855	2.53	0.112
likelihood ratio-model χ^2	67.17		
χ^2 significance (p-value)	0.000[a]		

Notes:
This table reports the factors that differentiate between 332 successful and 536 unsuccessful new buy recommendations issued by the top 10 brokerage houses between January 1, 1997 and December 31, 2002 with full analyst research reports available taking into account potential interactaction between conflict of interest and conflicts of interest variables. A new buy stock recommendation is defined as successful if it outperforms the benchmark by > = 10%, and unsuccessful otherwise. The following logistic regression model is run where SUCCESS = 1 if a successful new buy recommendation is issued, and 0 if an unsuccessful buy is issued. Refer to Table 5 for description of the independent variables.
[a,b,c,d] indicate significance at the 0.1%, 1%, 5% and 10% levels respectively.
The Wald statistic is adjusted for the fact that there are several observations from the same firm by dividing by 1.42, the average number of observations per firm.
Our logistic model is specified in equation (4) as follows:

$$\begin{aligned}\text{RATING} &= \text{LOGIT}(\pi) = \text{LN}\left(\frac{\pi}{1-\pi}\right)\\ &= \alpha + \beta_1\text{OPTIMISM}_{j,t} + \beta_2\text{PRICE\_MOM}_{j,t-1} + \beta_3\text{BTOM}_{j,t-1}\\ &\quad + \beta_4\text{OPTIMISM}_{j,t} * \text{INVEST\_RELATE1}_{j,t}\\ &\quad + \beta_5\text{PRICE\_MOM}_{j,t-1} * \text{INVEST\_RELATE1}_{j,t}\\ &\quad + \beta_6\text{BTOM}_{j,t-1} * \text{INVEST\_RELATE1}_{j,t} + \beta_7\text{OPTIMISM}_{j,t}\\ &\quad * \text{ INVEST\_RELATE2}_{j,t} + \beta_8\text{PRICE\_MOM}_{j,t-1} * \text{INVEST\_RELATE2}_{j,t}\\ &\quad + \beta_9\text{BTOM}_{j,t-1} * \text{INVEST\_RELATE2}_{j,t} + \beta_{10}\text{ANALY\_FOLL}_{j,t} + \varepsilon_{j,t}.\end{aligned}$$

and, most importantly, facilitating investment banking transactions, the issue directly addressed by regulators (e.g., Kadan et al., 2009). We in fact find empirically that both analyst overoptimism, as measured by the tone of their report, *and* conflicts of interest distinguish between new buy and new sell recommendations. This is consistent with the perception that analysts make reality look better than it is, even though the evidence is that they get the majority of their new buy recommendations wrong. This argument parallels that in other studies (such as Francis and Philbrick 1993; Lin and McNichols, 1998; and Hong and Kubik, 2003) which document that analysts issue optimistic forecasts in response to their incentives. In the case of stock recommendations and in line with the effect of the recent regulations (i.e., NASD 2711 as documented in Kadan et al., 2009) it is more likely that analysts issue optimistic recommendations in order to obtain and maintain investment banking corporate transactions from which they derive economic incentives in the form of huge pay and bonuses.

Although we find no evidence of analyst overconfidence as proxied by the certainty of their reports, in addition to analyst overoptimism, the existence of representativeness bias associated with new buys is evident. In particular, prior stock momentum and growth stock characteristics are statistically significant in explaining analyst buy as opposed to sell stock ratings. Our findings echo the conclusions of Stickel (2000), and Jegadeesh et al. (2004) that analysts prefer stocks with 'best' characteristics.

Importantly, as indicated already, we also find potential conflicts of interest, as measured by investment banking relationships with the firm the analyst is following, have a very significant impact on the type of recommendation made. Our results thus appear to justify recent regulations governing analyst and brokerage house activity. This is further emphasised by finding that analysts are even more optimistic in their buy recommendations in the presence of potential conflicts of interest. Our findings are also consistent with Lin and McNichols (1998), and other studies (e.g., Barber et al., 2007; Kadan et al., 2009; and Agrawal and Chen, 2008) conducted after the implementation of NASD 2711.

In additional analyses, we examine whether analyst cognitive bias and potential conflicts of interest can help explain why sell-side analysts may get certain recommendations right and others wrong. We find that unsuccessful buy recommendations are characterized by clear evidence of the operation of the representativeness heuristic, in particular in terms of the 'good company, good stock' syndrome. Stocks analysts get wrong have higher momentum, are larger, have growth characteristics, and higher analyst following. Importantly, they are also more likely to be associated with strong links with the analyst's investment bank. However, although there is some weak evidence that analysts may be more likely to suffer from behavioural bias in the presence of acute potential conflicts of interest for large firms in the case of new buys they get wrong, nonetheless, independent of such threats, we provide clear evidence of how, in particular, representativeness cognitive bias can help explain new buy stock recommendations that analysts get wrong. On the other hand, there is little evidence of such factors at work in driving analyst new sell recommendations that are successful or not. Interestingly, we find our results are robust across bull and bear market conditions.

Rules implemented to date effectively only seek to address the optimism in analysts' recommendations arising from corporate relationships investment banks have with firms. This suggests that the SEC and others believe that the problem of optimistic stock recommendations is predominantly caused by analyst incentives associated with conflicts of interest issues. Our study addresses the problem of optimistic analyst stock ratings from a broader perspective, and shows that there are other factors over and above conflicts of interest that contribute to this problem, in particular, analyst cognitive bias in the form of overoptimism and representativeness bias. In fact, such factors are arguably inherent in the analyst's job, and, as such, may be difficult to eliminate. These problems are far more salient in analysts' new buy recommendations than in their new sell counterparts. This suggests that analyst buy recommendations, in particular, will continue to lack investment value however successful the regulatory changes enacted.

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