CRANFIELD UNIVERSITY

THABANG MOKOALELI-MOKOTELI

ARE ANALYSTS BIASED? AN ANALYSIS OF ANALYSTS' STOCK RECOMMENDATIONS FOR STOCKS THAT PERFORM CONTRARY TO EXPECTATIONS

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THABANG MOKOALELI-MOKOTELI

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SUPERVISOR: PROFESSOR RICHARD TAFFLER

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Abstract

The finance literature suggests that analysts' stock recommendations have negligible impact on market prices. Some studies suggest this lack of market impact may be partly driven by the affiliations between investment banks and the firms their brokerage arms cover (conflicts of interest). However, most of these studies fail to take into account other factors including institutional and trading issues and psychological biases which may well be just as important in influencing analysts when they gather, process and interpret information about stocks.

The aim of the current study is to establish the factors which are associated with analysts issuing stock recommendations that lack market impact. I find that nonconforming analysts' stock recommendations are associated with overconfidence bias (as measured by optimism in the language they use) and representativeness bias (as measured by previous stock price performance, market capitalisation, book-to-market and change in target price). Thus, stocks that receive a buy rating and subsequently underperform the respective benchmark are associated with a high level of optimism in the tone of the language used by analysts in their investment reports that they prepare to justify their recommendations, have positive previous price momentum, have large market capitalisation, have low book-to-market ratio and have their target prices changed in the same direction as the stock recommendation. Not surprisingly, there is also a relationship between the investment bank issuing the recommendation and the firm. In addition, stocks that are awarded sell rating and subsequently outperform the benchmark have characteristics opposite to those of nonconforming buys.

Finding that potential conflicts of interest significantly predict analysts' nonconforming stock recommendations supports recent policy-makers' and investors' allegations that analysts' recommendations are driven by the incentives they derive from investment banking deals. These allegations have led to implementation of rules governing analysts' and brokerage houses' behaviours. However, finding that cognitive biases play a major role in the type of recommendation issued suggests that these rules may work only in as far as regulating conflicts of interest, but will have a limited role in regulating psychological bias, as my results suggest that analyst bias is inherent in their work. Surveys of what fund managers expect of analysts indicate low rankings of analysts' investment advice as manifested in their recommendations (e.g., All-America Research Team Survey 2002). My results further indicate that fund manager concern is likely to continue because not all behavioural factors in analyst stock recommendations can be controlled.

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Chapter 1

1.1   Introduction

This chapter introduces the thesis, its research aims and the rationale for focusing on the stock recommendation nexus. The chapter consists of six sections. Section 1.2 presents the background of my research. Section 1.3 presents the research questions. Section 1.4 presents my research objectives in relation to the research gaps which this thesis seeks to fill. Section 1.5 provides justification for focusing on stock recommendations. Section 1.6 outlines my research approach. Section 1.7 provides a brief overview of the conclusions drawn from the research and Section 1.8 outlines the structure of the chapters that follow.

1.2   Background of the research

Investment banks are key participants in the equity markets. Their main functions include issuing securities on behalf of companies and governments, trading securities in the primary and secondary markets on behalf of individual and institutional investors, managing portfolios for clients and providing other financial advice and support services (Haugen, 1997; Bodie et al., 1999). Traditionally, the activities of investment banks are grouped into corporate finance, brokerage services and proprietary trading (Michaely and Womack, 1999).

Sell-side analysts form part of the research group in the brokerage arm of the investment bank. Their main task is to gather information on the industry or individual stocks from customers, suppliers and firm managers, analyse this data, form earnings forecasts and make stock recommendations (Michaely and Womack, 1999) and price forecasts. The role of securities analysts in the brokerage firm can be viewed as a marketing aid to brokers because they provide tools (i.e. forecasts and recommendations) that help brokers maximise revenues (Chung, 2000) and sales efforts (Brennan and Hughes, 1991).

Some studies highlight the importance of analysts' information gathering activities in the pricing of stocks in financial markets. Grossman and Stiglitz (1980) show that stock

prices cannot perfectly reflect all information that is available, and therefore analysts devote enormous resources to gathering new information. Analysts deserve to be compensated as information gatherers. Beaver (2002) indicates that efficient analyst information processing facilitates efficient security price setting while Fernandez (2001) shows that analysts produce information that is the "life-blood" of both the market and the individual investor.

1.3   Research problem and research questions

Although research attests to the importance of financial analysts for the efficient functioning of the stock market, in the recent past there have been some doubts about the credibility and objectivity of analysts' stock recommendations. Specifically, there was concern that analysts' recommendations were overly optimistic and did not seem to reflect the true beliefs about the value of the stocks. Around mid-2000, the percentage of buy recommendations reached 74% of the total recommendations outstanding while the percentage of sells fell to 2% (Barber et al., 2004). There are various reasons that policy-makers, investors and researchers believed might be responsible for the unequal distribution of buy and sell recommendations. For instance, some studies argued that analysts would be denied access to management if they issue pessimistic recommendations. Denying analysts access implies that analysts would not be able to obtain the private information from management which they needed to make decisions about the value of stocks. However, a more likely reason was probably because analysts' optimistic recommendations could earn their investment employers enormous fees on 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 other professional bodies. They responded by implementing regulations to govern brokerage firms and analysts. In September, 2000, the Securities and Exchange Commission (SEC) implemented Regulation Fair Disclosure (Reg FD). Reg FD was meant to curb the practice of asymmetric information provision where top executives in companies would disclose information to particular analysts, often to those working for investment banks with whom they have business relationships. In August, 2002, the National Association of

Securities Dealers (NASD) and SEC issued NASD 2711 and Rule 472 respectively. Overall, these two regulations require analyst research reports to display the proportion of the issuing firm's recommendations that are buys, holds and sells. In April 2003, the "Global Analyst Research Settlement" was reached between the top ten US brokerage firms and the SEC, New York Stock Exchange (NYSE), NASD and the New York Attorney General. According to this settlement, these brokerage firms had to pay huge penalties for any alleged misconduct that resulted in investors losing huge amounts of money from trading on their analysts' stock recommendations during the technology bubble.

Since the implementation of these regulations, there have been various studies carried out to test their efficacy, particularly in curbing the alleged conflicts of interest which were believed to be the main determinant of the disproportionate number of optimistic reports. Although there are certain studies that do not find evidence to support the implementation of some regulations such as Ke and Yu (2005), most of them (e.g. Barber et al., 2004; Madureira, 2004) conclude that the regulations do achieve their intended motives particularly with regard to restraining conflicts of interest. The question that is not answered by these studies, however, is whether conflict of interest is the one and only factor that influences analysts' stock recommendations or whether there are other factors in addition to conflicts of interest such as psychological biases that may be playing a role. This is the purpose of this thesis.

Research also finds that although analysts issued optimistic reports on most of the stocks they covered, their optimistic recommendations lacked 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 as a result of taking advice from analysts' recommendations. Womack (1996), on the other hand, finds that new "buy" recommendations of stock continue to go up for four to six weeks after the new stock recommendation is made while "sell" recommendations drift lower for six more months. His results suggest that the average level of recommendation has little investment value but changes in level are valuable although for a limited time. Ryan and Taffler (2005) find that only new "sells" and recommendations for smaller,

less followed stocks have investment value. From the findings in these studies, the question that comes to mind is, what could have influenced analysts to issue recommendations that lack necessary market impact?

Other studies allude to the fact that information which analysts actually use differs from that used to justify their recommendations (e.g., Breton and Taffler, 2001; Amir et al., 1999; Rogers and Grant, 1997). It seems analysts use non-financial, qualitative data that is not found in companies' financial statements. If analysts do not rely exclusively on the companies' reports, then where do they get information from that they use to make their recommendations?

Bradshaw (2002) documents that analysts frequently justify recommendations with target prices and that, not surprisingly, analysts issue more favourable recommendations for stocks with higher target prices relative to current prices. Brav and Lehavy (2003) and Asquith et al., (2005) document a significant market reaction to a change in target prices, both unconditional and conditional on contemporaneously issued stock recommendations. However, these studies do not establish a clear link between recommendations and target prices so that we can clearly understand what the role of target prices that are issued concurrent with stock recommendations is.

The research problem addressed in this research is: What are the factors that are associated with stock recommendations which do not perform as expected? Essentially I argue that nonconforming analysts' stock recommendations are not associated with conflicts of interest alone but with other factors such as previous performance of the stock. The factors that are hypothesised to be influencing analysts' nonconforming stock recommendations are classified mainly into overconfidence bias, representativeness bias and corporate relationships between investment banks and firms. I basically investigate the factors driving new buy and sell stock recommendations but where the stocks themselves subsequently perform in an extreme opposite direction to the one expected.

1.4   Research objectives

Specific objectives of this study are summarised as follows:

- To explore whether analysts' stock recommendations in the recent period still have limited economic value using an appropriate return-generating model.

- To determine the factors underlying analysts' stock recommendations that render them less effective.

- To develop and test a model that can predict and explain analysts' outputs, specifically, their nonconforming stock recommendations.

1.5   Rationale for focusing on stock recommendation nexus

There are various reasons why analysts' recommendations are particularly interesting. First, issues relating to analysts' biased recommendations are highly topical and of considerable public policy importance. In particular, analysts' recommendations have received substantial public attention because of the role that analysts played in the bankruptcy of Enron and their conflicts of interest debacle, as investigated by the New York Attorney General and the SEC and the subsequent implementation of rules and regulations to govern financial analysts and brokerage firms.

In the case of Enron, management used complex accounting methods that overstated earnings and concealed additional debt by setting up off-balance sheet partnership transactions. These were designed to boost the company's credit rating, its capacity to borrow and to raise its stock price beyond what would be justified by an objective valuation of the firm's underlying assets and profitability. At the same time, Enron's executives were deriving millions of dollars from the same partnerships. Enron's nefarious practices have raised questions about accounting principles, auditing disclosures and corporate governance and it is glaringly clear that investors used unreliable and inaccurate information (Federal News Service, February 12, 2002). Despite analysts' tacit task of gathering information about companies, they were not

able to pick up the accounting schemes used by Enron. As a result, 19 out of 22 sell-side analysts continued to recommend "buy" right up until the large fall in Enron's stock and its ensuing bankruptcy (The Investment Dealers' Digest: IDD, May 27, 2002). It is debatable whether analysts were genuinely unaware of Enron's accounting schemes due to the fact that they were unable to read and interpret its financial statements, or whether they were fully aware but decided for some other reason to ignore the situation.

It could be argued that although management had made efforts to conceal its activities in the company's financial statements, there were plenty of clues that should have made analysts aware of the situation early enough. After all, that is what analysts are paid to do. It is especially striking that in addition to their inability to detect Enron's accounting machinations, no analyst downgraded Enron neither after the chief executive's surprise resignation, after revelations about repeated Enron stock sales by company executives, nor after news stories that raised questions about Enron's balance sheet (Financial Post, March 2, 2002).

On the issue of analysts' conflicts of interest investigated by the New York Attorney-General, analysts were found to make "buy" and "strong buy" recommendations for stocks which were not necessarily undervalued but were recommended because their investment bank employers could earn enormous fees on corporate finance transactions. Analysts would also be rewarded for their part in promoting these deals via additional compensation. In particular, Merrill Lynch research analysts were accused of misleading investors by issuing "flattering" research reports to generate investment banking business. More than 30,000 emails were revealed where Merrill Lynch analysts were privately defaming companies while publicly telling investors to buy the shares (Financial Times, April 10, 2002).

This behaviour was largely blamed on the compensation structure of analysts. Clearly, major Wall Street firms needed to take immediate steps to reform analysts' compensation structures. As long as analysts were paid based on banking deals they generated or worked on, there would always be a question over the recommendations they made (Federal News Service, Feb 12, 2002). Eventually, Merrill Lynch agreed that

the firm should strengthen the 'Chinese wall' between analysts and its investment banking business, and compensate analysts based on the quality of their recommendations (Investor Relations Business, June 3, 2002). The separation of research and corporate finance was meant to ensure that recommendations made by analysts are not influenced by the economic incentives that arise from their firms investment banking deals. However, some observers believe that the agreement to separate investment banking and research is less likely to change the investment corporate culture because analysts are still not entirely independent of investment bankers (Financial Times, May 23, 2002). The insistence on the separation of the two roles serves to attest to the key role of the recommendation itself in analyst activity.

To date Rule NASD 2711 and Rule 472 have been implemented by the SEC and NYSE respectively. In general terms, they both require analyst research reports to display the proportion of issuing firms' recommendations that are buys, holds and sells. Rule 472 specifically addresses the issue of analysts' compensation. Studies to date (e.g. Barber et al., (2004) and Madureira (2004) show that these two rules are, to some extent, effective in attaining their objectives.

The second reason why analyst stock recommendations are interesting is that they are viewed as a key input to investors' decision-making processes. Hirst et al., (1995) analysed investor reactions to financial analysts' research reports and concluded that in using this information, investors take into account the incentives facing analysts in making their investment recommendations when judging the likely future performance of stocks and pay great attention to the strengths of the arguments underlying analysts' recommendations. Dugar and Nathan (1995) and Michaely and Womack (1999) show that investors discount the optimism exhibited in investment banker analyst research reports. Krishnan and Booker (2001) suggest that the information provided by analysts to support their recommendations reduces the tendency of investors to sell winners too soon and hold losers too long.

The third reason is that, conversely, surveys of what fund managers expect of analysts indicate low ranking of analysts' investment advice as manifested in their

recommendations while company and industry knowledge and 'other factors' are rated more highly (e.g., All-America Research Team Survey 2002 – Institutional Investor website). Fund managers also emphasised among other requirements the importance of "trustworthiness". The emphasis on factors other than the stock recommendation could be an explicit recognition that the analyst's recommendation is variously either (a) not to be trusted, (b) biased or (c) of no empirical value. Many institutional investors have now established their own research departments to conduct analysis in-house because of the perceived lack of professionalism in the way sell-side analysts do their jobs (Boni and Womack, 2001). The fact that institutional investors deem it necessary to incur the substantial expense of conducting analysis in-house is an indication that expert investment advice as proxied, in principle, by analyst stock recommendations, is key to them, but that they cannot place as much reliance as they previously did on the sell-side analyst any more.

Lastly, the extant empirical research evidence attests to the lack of investment value of analysts' stock recommendations in general. However, these studies do not provide a reason for this lack of market impact. The aim of this study is to establish the factors which may be playing a major role in influencing analyst stock recommendations to lack market value, in particular, the role of analysts' cognitive biases. *Inter alia*, I draw on the recent study by Fogarty and Rogers (2005). They use *Diction* in conjunction with other content analysis software to study financial analysts' reports and conclude that analyst' reports are characterised by bias, skew and lack of science. They suggest that in order to understand financial analysts and their job, we need also to analyse their textual data. With this suggestion in mind, I build on their study by using analysts' textual data to measure their psychological biases together with other key empirical measures of factors driving their investment recommendations.

1.6   Research approach

This section provides a brief overview of the methodological features of the current study. The research approach adopted draws on the previous studies which evaluate the performance of analysts' stock recommendations using event study methodology. In the first instance, this study sets out to test seven hypotheses (chapter 3). These hypotheses

are basically testing whether factors that proxy for overconfidence bias (OPTIMISM, CERTAINTY), representativeness bias (ACTIVITY, PRICE_MOM, FIRM_SIZE, BTOM, TGTPRC_CHNG) and relationship between investment banks and firms (INVEST_RELATE) have any impact on analysts' nonconforming stock recommendations.

There are four stages in my research. In the first stage, performance of stock recommendations and target prices is evaluated using event study methodology where the event date is identified as the date that a stock recommendation is changed from its previous category to new buy or new sell categories. Cumulative buy-and-hold abnormal returns are measured over the subsequent twelve month period using the reference portfolio return generating benchmark to estimate expected return. Chapter 4 provides a full description of how the evaluation process is carried out.

In the second stage, new buy and new sell recommendations associated with subsequent stock performance in an opposite direction to the one expected are selected for further analysis. These recommendations that perform contrary to expectations are classified as recommendations lacking market impact. Chapter 7 presents the performance of stocks that are awarded a buy and a sell rating and how I selected my conforming and nonconforming stock recommendations.

In stage three, I employ logistic regression analysis to test for the factors that might be associated with such buy and sell recommendations that lack market impact. RATING is the dependent variable and takes the value 1 if the recommendation is a new buy which significantly underperforms the benchmark and 0 if the recommendation is a new sell that significantly outperforms the benchmark. Chapter 8 describes the procedure I use and the results of this stage of my research.

The last part of my thesis is similar to stage 3. However, I specifically test for representativeness bias in analysts' nonconforming stock recommendations using only stock based characteristics, which are momentum, size and book-to-market, while analyst following serves as a control variable. Again using logistic regression, my

dependent variable is RATING. RATING takes the value 1 if a buy recommendation underperforms the benchmark and 0 otherwise. Chapter 9 provides complete information on how the analysis is conducted and the empirical results.

1.7   *Overall conclusions*

The findings in this study show that there are certain factors that are associated with analysts' nonconforming stock recommendations. I hypothesise that the main drivers of analysts' nonconforming stock recommendations are their psychological biases (in particular, the overconfidence and representativeness biases) and corporate relationship existing between investment banks and firms. There is evidence in support of overconfidence bias (as measured by *Diction* variable Optimism). The overconfidence bias found in analysts' research reports is interpreted as showing that analysts believe they have superior investment abilities and tend to overestimate the likely performance of the stocks they follow. This argument is consistent with other studies such as those of Odean (1998b); Barber and Odean (2001) and Massey and Thaler (2005) who document that when investors are faced with difficult tasks they tend to overestimate the precision of their information and thereby become overconfident.

My results further show that, in addition to overconfidence, other factors that serve as measures of representativeness bias (i.e., previous price performance, size of the firm, book-to-market and target prices) and corporate relationships play a major role in influencing nonconforming stock recommendations that analysts issue. The logistic regression results show that if the stock has done well in the past, has large market capitalisation, has low book-to-market ratio (i.e., is 'growth' stock), has the target price changed in the direction of the stock recommendation and has corporate relationship with the investment bank for which the analyst is working for, then it is likely that the analyst will issue a buy recommendation which will subsequently not perform as expected. The reverse holds true for new sell recommendations that outperform the benchmark. However, I need to point out that no analysis is performed to establish whether stocks that perform as expected have the opposite characteristics, as the thrust of this research is specifically to establish factors underlying stock recommendations that perform contrary to expectations.

The preference for stocks that have positive previous price performance, large market capitalisation and low book-to-market ratio is consistent with the findings of Stickel (2000) and Jegadeesh et al., (2004). This is also in line with the representativeness bias argument of Solt and Statman (1989), Shefrin and Statman (1995) and DeBondt and Thaler (1985) that analysts believe that past good performance and large market capitalisations represent good future performance.

Although I hypothesise that target price is a proxy for representativeness bias, it actually appears to be a very difficult variable to interpret as it is highly correlated with stock recommendation. This may be a reason why other studies (e.g., Brav and Lehavy, 2003 and Asquith et al., 2005) have studied both target prices and stock recommendations together. It may actually be that target prices are not proxies for representativeness bias *per se*, but as Asquith et al., (2005) put it, only serve to peddle the stocks for which analysts issue buy (sell) recommendations.

My finding, that conflicts of interest (as measured by INVEST_RELATE) are associated with nonconforming stock recommendations that analysts issue, supports recent policy-makers' and investors' allegations that analysts' recommendations are driven by the incentives that analysts derive from investment banking deals. It also justifies the recent implementation of the new rules to govern analysts and brokerage firms. However, given that I find other factors influencing analysts other than their conflicts of interest, it is likely that the rules will have a limited effect in curbing analysts' overconfidence and representativeness biases which appear to be inherent when analysts issue their recommendations particularly those recommendations that lack market impact.

1.8   *Structure of the thesis*

This thesis comprises ten chapters, with chapters 8 and 9 containing my empirical results. **Chapter 1,** this chapter, has introduced the background to my research as well as my research questions and thesis area of focus. The objectives of the current research and the justification for concentrating on the stock recommendations nexus are then

presented. An overview of the research approach is then outlined followed by the snapshot of overall conclusions.

Chapter 2 presents the extant literature on the role of analysts in the stock market and the role of analysts in the documented market anomalies relevant to my thesis. The role of analysts in the stock market is anchored in traditional finance literature while the literature on market anomalies is, *inter alia*, linked to recent developments in behavioural finance research. The second part of this chapter provides my conceptual framework built from these two strands of the literature. The conceptual framework addresses the research questions and research objectives by defining the hypothesised factors driving analysts' stock recommendations that lack market impact. The final part of this chapter identifies the gaps in the literature followed by the presentation of my research questions.

Chapter 3 presents my hypotheses and the variables used to test these hypotheses. I have seven null hypotheses. Null hypotheses 1 and 2 test for overconfidence (as measured by Optimism and Certainty) and representativeness biases (as measured by Activity) using the tone of language that analysts use in their research reports which they prepare to justify their recommendations. Null hypotheses 3 to 6 test for whether previous stock performance, size of the firm, book-to-market and target prices have any influence on the issue of stock recommendations that lack market impact. All these factors are used as measures of analyst representativeness bias. Null hypothesis 7 measures the effect of corporate relationships existing between investment banks and firms on the type of recommendation that analysts issue.

Chapter 4 presents the methodological approach I have adopted in this study. It commences by discussing the methodology employed to evaluate the performance of stock recommendations and target prices so that I can identify those stock recommendations that have not performed as expected. The method for selecting nonconforming stocks is then discussed followed by the presentation of the content analysis method used to process analysts' textual data. The chapter ends with a summary.

Chapter 5 presents my pilot study. This chapter is used to test whether I can generate operational measures of analyst bias from analysis of their investment circulars using *Diction* software. The chapter starts by discussing the pilot study objectives and data, followed by the pilot study results. Discussion and summary concludes the chapter.

Chapter 6 provides my sample selection process, details of the data and description of the stock recommendation and target price characteristics of my sample data over the time period starting from January 1997 to December 2003. Specifically, the first part of the chapter presents information on the sources of the data used in this study and the data itself. The second part shows how the final sample is selected, and the final part describes the final samples of stock recommendations and target prices I use in subsequent analysis.

Chapter 7 analyses the subsequent market reaction to changes in stock recommendations and target prices over the sample period and different sub periods. It then presents the numbers of new buy and new sell recommendations that are not performing as expected in order to identify the appropriate cases to employ in the main empirical analysis conducted in the next chapter. Summary and discussion end the chapter.

Chapter 8 empirically investigates the factors that are associated with analysts' nonconforming stock recommendations by using logistic regression analysis. The factors tested for are as postulated by the conceptual framework I establish in chapter 2 section 2.4 and are mainly measures of analysts' cognitive bias and corporate relationships. The chapter starts by providing a description of both new buy and new sell recommendations that lack market impact, and then presents the results of logistic regression when hypothesised factors that influence nonconforming analysts' stock recommendations and control variables are used as regressors. The dependent variable is RATING. RATING equals 1 if analysts issue buy recommendations which subsequently underperform the respective benchmark by at least -20% and 0 if analysts

issue sell recommendations which subsequently outperform the respective benchmark by at least +20%.

Additional analysis using linear regression analysis is carried out to investigate whether the factors that drive stock recommendations that lack market impact may also explain the target prices issued concurrently with stock recommendations.

Chapter 9 uses a larger sample size (compared to the sample size in chapter 8) to test the null hypotheses 3, 4 and 5 in chapter 3. The aim is to investigate the role of representativeness bias (as measured by momentum, size and book-to-market) in analysts' nonconforming buy and sell recommendations during the whole sample period, during the bull and the bear markets, and before and after the implementation of NASD 2711. The main reason why only three hypotheses are tested is to obtain a clearer picture of the role of representativeness bias in analysts' stock recommendations.

The chapter starts by presenting the characteristics of nonconforming new buy and new sell recommendations and then presents the logit results of the factors differentiating between nonconforming buy and sell recommendations. Additional analyses are carried out to establish whether the factors differentiating between nonconforming buys and sells are similar or are different during the bull and the bear markets, as well as before and after the implementation of NASD 2711.

Chapter 10 summarises the findings of my study and draws conclusions relating to my original research questions. The practical and theoretical implications as well as an acknowledgement of its limitations are also presented and suggestions for future research are provided.

My contribution to knowledge is also evaluated. My thesis provides evidence that adds to current concerns regarding the factors that drive analysts' stock recommendations and whether conflict of interest is the only such factor. I find clear evidence that analysts' stock recommendations are driven by other factors (e.g., analysts' overconfidence (as measured by optimism in the language they use) and

representativeness (as measured by stocks' previous price performance, firm size, book-to-market and target price changes) in addition to conflicts of interest. These findings imply that the regulations that have been deployed to govern analysts and brokerage firms, however successful in dealing with analysts conflicts of interest, may have limited impact on analysts' overoptimistic behavioural biases which are probably inherent in the nature of the task.

In summary, this chapter has laid the foundation for my thesis. It introduces the overall research problem and research questions. It establishes the importance of my research and its original contribution to knowledge. The research approach is described, the thesis outline is presented and overall conclusions are briefly presented. Subsequent chapters build on this foundation commencing with the next chapter, Literature Review.

Chapter 2 Literature review

2.1   Introduction

This chapter summarises previous work related to the current study. Two strands of literature are examined: (a) the role of financial analysts in the stock market and (b) financial analysts' behaviour and market anomalies. Although these two sets of literature are closely related, they are often explored separately. I therefore follow the same practice in this review.

The chapter is organised as follows: section 2.2 looks at the role of analysts in the stock market, section 2.3 summarises the role of financial analysts in the documented market anomalies literature, and section 2.4 presents the conceptual model.   Section 2.5 presents the chapter summary, then identifies gaps in the literature and then formulates the research questions.

2.2   The role of analysts in the stock market

Research shows that financial analysts are essential for the efficient operation of the stock market. However, in the recent past, doubt has arisen about the credibility of financial analyst outputs, particularly their stock recommendations. This section summarises the vast amount of literature on the role of analysts in the financial markets, highlighting the aspects relevant to the current study such as how efficient and effective they are in their work, their conflicts of interest and the efficacy of rules and regulations established to govern and regulate brokerage firms and financial analysts.

2.2.1   Function of analysts

There are two classes of analysts: sell-side analysts and buy-side analysts. Sell-side analysts gather and evaluate information from public and private sources, generate forecasts on companies' earnings and future prospects, and make recommendations that lead to buying or selling of the companies' securities by investors.

On the other hand, buy-side analysts work for institutional investors such as mutual funds, hedge funds or investment advisors. Unlike sell-side analysts, buy-side analysts

do not produce research reports for the public since their work product is the proprietary possession of their employers. Buy-side analysts effectively use research reports produced by sell-side analysts to help make their own assessments. Their research reports typically contain both investment recommendation and the supporting arguments. This study concentrates solely on sell-side analysts.

Michaely and Womack (1999) categorise the specific information dissemination role of analysts as gathering information on the industry or individual stocks from customers, suppliers and firm managers; analysing this data and forming earnings estimates and making stock recommendations; and presenting recommendations to buy-side analysts and fund managers in presentational and written form. The ultimate goal of this process is to find the "fundamental" price of the company's stock and then to compare this with the actual price to see if the stock is overvalued or undervalued. Stock recommendations are arrived at in two ways: through analysts' anticipated changes in company fundamentals, in reaction to new news, or company reports such as earnings releases (Michaely and Womack, 2003). Evidence on analysts' response to company reports is confirmed by Womack (1996) who finds that approximately 12% of recommendation changes were within one day of quarterly earnings reports in the 1989-1991 time period.

Beunza and Garud (2004) present a slightly different view of what the role of financial analysts in the financial market is. They show that analysts provide a road map and a representation scheme in a phenomenon that is inherently fuzzy and emergent. Therefore, "by offering intermediate metrics, the appropriate network of connections and temporary comparisons, analysts' frames facilitate transactions especially when there is no certainty out there" (p. 34). Regardless of how their roles are defined, financial analysts are expected to conform to individual firm and industry guidelines and codes of professional conduct for the preparation and dissemination of their research reports (Fernandez, 2001).

Financial analysts' research reports contain textual information that analysts use to justify the recommendations they award stocks. Other information such as target prices and earnings forecasts are found in the research reports as well. Asquith et al., (2005)

show that the stronger the justifications provided in the report, the stronger the market reaction to the report. Their results suggest that the words or the tone of language that analysts use to justify their reports is essential to the investors. However, the content analysis method that they use is not entirely objective, and also they concentrate on the market reaction to the research reports whereas in the current study, the content analysis method used to analyse the tone of language used by analysts to justify their recommendations is completely objective and is aimed, not only at assessing the type of information contained in the research reports, but at linking the tone of language that analysts use to the cognitive biases to which they may be prone when they do their work.

Fogarty and Rogers (2005) suggest that academic research should not concentrate on the direction of analysts' bottom lines (i.e., stock recommendations and earnings forecasts) but should conduct textual analysis as well. In their study, they examined financial analysts' textual data and conclude that analyst output is characterised by three elements: influence, skew and lack of science. The content analysis method they use is objective and my thesis draws largely from their study. However, in their study they are only analysing and evaluating analysts' research reports while in this study I analyse the research reports and attempt to link the tone of the language used to the type of recommendation issued.

2.2.2   *Information used by analysts*

Analysts use various sources of information to draw up their recommendations. Typically, they use both financial and qualitative information found in companies' annual reports. Breton and Taffler (2001) demonstrate that profit-based information is of importance and balance sheet information is much less important, if at all. However, Breton and Taffler (1995) discover that analysts' ability to interpret "window-dressing" is very low. Only 3.1% of such schemes are picked up by a sample of skilled investment analysts, although 60% believed that they had corrected for such schemes in their analysis.

Crucially, analysts rely on non-financial, soft, qualitative and imprecise information in their primary task of making stock recommendations. Consideration of a firm's management and strategy, although occupying only a small part of analysts' reports, is the key single determinant (Breton and Taffler, 2001). Rogers and Grant (1997) assert that financial reports provide 52% of the information cited by analysts and 48% is external to the financial reporting process. Cornell (2001) observes that analysts do not compare stock prices to fundamental value in their analysis and concludes that analysts stock recommendations are based on something other than a comparison of market price and fundamental value.

Krische and Lee (2000) investigate the relation between analyst stock recommendation and eight quantitative variables found to have predictive power on future returns in prior research. They conclude that analysts' stock recommendations capture qualitative aspects of the firm's operations that do not appear in the quantitative signals they examine. Amir et al., (1999) observe that the explanatory power of broad-based financial statement data has decreased and analysts are learning less from the financial data. Similarly, Bradshaw (2004) documents that analysts do not use present value valuation models to make stock recommendations, but instead rely on valuation heuristics. But without using companies' financial statements extensively, would analysts' reports be sufficiently informative? Frankel et al., (2002) observe that the informativeness of analysts' reports increases when brokerage profits are higher (i.e., higher trading volume and higher volatility) and when they reveal 'bad' news, and decreases when information processing costs are increased.

Some studies note some shortcomings in the valuation of companies by analysts. According to Cornell (2001), analysts concentrate on the short run performance of companies, not on fundamental value. Furthermore, he notes that the discussions of fundamental value in their research reports are vague and nebulous and rarely involve the presentation of a precise, quantitative model that can be dissected and critiqued. Because of the lack of an explicit valuation model, it is difficult to understand how analysts arrive at their estimates of fundamental value and to discern how and why those estimates might change in response to events. What is even more interesting is

that analysts' stock recommendations appear to be pro-cyclical in nature. When bad news is announced, analysts will recommend a "sell", and when good news is announced they recommend a "buy". This point is further substantiated by Juergens (1999) who notes that analysts react to firm announcements after the news is released on the wires, either by adjusting their earnings forecasts or by revising their investment recommendations. The findings of Juergens (1999) are further supported by Conrad et al., (2004) who document that large price changes are associated with more frequent changes in analysts' recommendations and that "forces other than direct price-to-value comparisons have an impact on analyst recommendations"(p. 27).

Overall, most of these studies allude to the fact that information which analysts actually use differs from that used to justify their recommendations. It seems analysts use non-financial, qualitative data that is not found in companies' financial statements. However, none of these studies on the information used by financial analysts shows clearly which exactly are the qualitative factors influencing analysts' decisions on stock recommendations. The objective of this study is to establish some of these factors, particularly for stocks that do not perform as expected.

2.2.3 *Analysts' following and herding behaviour*

Different stocks have different levels of analysts' coverage. The number of analysts following a stock appears to vary according to certain factors. Bhushan (1989) conjectures that analysts will decide to cover firms by weighting the costs of effort expended in information gathering against the benefits of brokerage commissions. Bhushan (1989) and Hussain (2000) observe that the number of analysts following a stock is positively related to the number of institutions holding the firm's shares, the percentage of the firm held by institutions, firm return variability and size. For example, large firms are found to have a larger analyst following than small firms. Lang and Russell (1996) document a positive association between analyst following and analyst forecast accuracy.

Alford and Berger (1999) model analyst following, forecast accuracy and trading volume as simultaneous determinants of the firm's information environment. They find

that analyst following is positively associated with accuracy and trading volume and higher for regulated industries. Characteristics of the analyst's job play a role in inducing coverage. For instance, analysts face start-up costs (McNichols and O'Brien, 1997) such as learning about the firm's products (Mikhail et al., 1997).

Merton's (1987) theory of information dispersal suggests that if investors rely on brokers to learn about their investment options, then firms with wider coverage will be more valuable because of a larger investor base knowing of the investment opportunity. Various studies support Merton's theory, demonstrating that firms with more analyst coverage have lower trading costs (Brennan and Subrahmanyam, 1995) and greater trading volume (Alford and Berger, 1999).

Chen et al., (2002) investigate the impact on company valuation of the affiliation of analysts and the type of recommendation they make. They show that the quantity and breadth of coverage that national brokerage firm analysts (as compared with regional brokerage firm analysts and independent houses) can bring to bear in the market has the greatest effect on company value. However, when buy recommendations are isolated from the other types of recommendation (i.e., hold and sell), independent house firm analysts have the greatest positive impact on stock prices because of their higher perceived credibility.

Most analyst following studies concentrate on the company characteristics which can explain the number of analysts following their stocks. However, these studies do not address the issue of whether analyst following has any bearing on the type of recommendation issued. Effort is made in this study to establish the effect of analyst following on the type of stock recommendation that financial analysts issue.

Prior research has also found that analysts' forecasts are affected by their herding behaviour where analysts make their personal forecasts more consistent with prevailing forecasts. Welch (2000) finds that analysts' earnings revisions have a positive influence on the next two analysts' revisions. Cote and Goodstein (1999) document that the objective of herding is to save one's reputation. Hong et al., (2000) show that older analysts are less likely to herd, both in choice of firms followed and deviation from earnings consensus. Herding behaviour among analysts raises ethical questions

particularly when analysts use others' opinions primarily to protect their reputations rather than provide more accurate forecasts (Cote and Goodstein, 1999). Although research on herding mostly relates to earning forecasts, it is a very common phenomenon in stock recommendations as well. This is why Bajari and Krainer (2004) conclude that peer group effect is important in explaining recommendations as opposed to relationships between brokerage houses and companies.

2.2.4   Analysts and stock recommendations

One of the most important tasks of financial analysts is to provide a rating on the stocks they follow, in which case they should have a clear perception what they think the future value of the stock will be. Like earnings forecast accuracy, predicting future stock price performance may be a difficult task for analysts. The semi-strong form of market efficiency argues that investors cannot profit from using publicly available information and, presumably, this includes recommendations made by financial analysts. However, according to Grossman and Stiglitz (1980) prices cannot perfectly reflect the information which is available, since, if it did, those who spent resources to obtain it would receive no compensation. This suggests the existence of a certain level of inefficiency in the market is necessary to warrant paying analysts as information gatherers. Fernandez (2001) confirms that security analysts produce information that is the "life-blood" of both the market and investors.

2.2.4.1   Economic value of stock recommendations

In the recent past, concern has been raised regarding the economic value of analysts' stock recommendations. There is a plethora of studies that attest to the fact that analysts' stock recommendations have economic value. Stickel (1995) finds that analysts are able to detect the extent to which a stock is overvalued or undervalued. He also finds that "buy" and "sell" stock recommendations have a profound effect on the stock return. Womack (1996) and Ryan and Taffler (2005) indicate that both sell and buy recommendations do have significant value. However, the recommendations take time to be absorbed by the market, particularly new sells. Barber et al., (2003) show that the more highly recommended stocks earned greater market-adjusted returns during the 1996-1999 period than did less favoured stocks and the opposite was true for 2000-2001

where highly recommended stocks performed poorly and least favoured stocks performed well. This was because analysts failed to forecast the reversal of the bull market in the year 2000, although there are problems in their methodology (Ryan and Taffler, 2005). Green (2003) focuses on the short-term informational advantage of brokerage firm clients and finds that analysts' recommendations do contain investment value even when transaction costs are controlled for. However, his findings suggest that profit is only made if clients have early access to the new recommendation. Other recent studies (such as Juergens, 1999, Asquith et al., 2005, Schlumpf et al., 2005, Agrawal and Chen, 2005) confirm the economic value of analysts' stock recommendations.

On the other hand, Barber et al., (2001) conclude that investors might not earn better than average net returns when trading on analysts' recommendations after taking into consideration risk and transactions costs. Similarly, Mikhail et al., (2004) show that after transactions costs, excess returns earned from identifying high performing analysts are insignificant. Fernandez (2001) states that in the past few years, it has been difficult for analysts to predict the future because of rapid structural change, greater uncertainty, sustained high volatility and irrational behaviour of the market.

Research has also examined whether other information issued by brokerage firms concurrent with recommendations have any economic value, in particular, target price (price forecasts). Bradshaw (2002) documents that analysts frequently justify recommendations with target prices and that analysts issue more favourable recommendations for stocks with higher target prices relative to current prices. However, it is not clear whether these target prices provide any information over and above information in stock recommendations (Michaely and Womack, 2003). Brav and Lehavy (2002) and Asquith et al., (2005) document a significant market reaction to a change in target price, both unconditionally and conditional on contemporaneously issued stock recommendation and earnings forecast revisions. Their results suggest that price targets have information content beyond what is contained in stock recommendations. Their findings further imply that stock recommendations should not analysed in isolation by investors but should be examined together with target prices.

Some studies have investigated whether the personal qualities of analysts have significant impact on the accuracy of their earnings forecasts and stock recommendations in terms of subsequent abnormal returns. Certain factors have been found to improve analysts' forecasting accuracy. Clement (1999) finds that forecast accuracy increases with experience and employer size while it decreases with the number of firms and industries followed. Stickel (1992) finds that "All-American" analysts' forecasts are more accurate than "non All-American forecasts". Mikhail and Walther (1997) find a positive relationship between accuracy and forecast experience. Jacob et al., (1999) investigate the contribution of experience and brokerage variables on analysts' forecasting attributes including forecast accuracy, frequency and horizon. They find that accuracy is positively associated with employer size and brokerage house degree of industry specialisation, and negatively associated with brokerage house turnover. However, they find no evidence that accuracy improves with experience. In a recent study, Tamura (2002) investigates how analysts' characteristics affect forecast errors and the results show that herd-to-consensus analysts submit earnings estimates that are not only close to the consensus but are also strongly affected by their personalities (optimism and pessimism).

Desai et al., (2000) document that stocks recommended by all-star analysts outperform benchmarks controlling for size and industry and stocks recommended by analysts focusing on a single industry outperform those recommended by analysts covering multiple industries. Chen and Cheng (2003) find similar results to Desai et al., (2000) with respect to all-star analysts, but they go further and establish that the market impact of recommendations, surprisingly, is stronger for inexperienced analysts than for experienced analysts after controlling for analyst-company specific effect. Mikhail et al., (2004) find that analysts whose recommendation revisions earned the most (least) excess returns in the past continue to outperform (underperform) in the future. Loh and Mian (2005) find that recommendations of superior earnings forecasters outperform the recommendations of inferior forecasters while Sorescu and Subrahmanyam (2004) conclude that experienced analysts offer more informative recommendations.

The general consensus seems to be that analysts' stock recommendations do have economic value and their value may be correlated to other factors such as analysts' personal qualities and other information contained in their research reports such as target prices. However, when taking into account risk and transaction costs, profit made by trading on analysts stock recommendations vanishes.

The key limitation of the existing studies on the value of analyst stock recommendations is that they evaluate future performance in general terms. For instance, studies such as Womack (1996) and Ryan and Taffler (2005) investigate the performance of new buy and new sell recommendations and conclude that in totality, they both (new buys and new sells) have an expected significant effect on stocks' future returns. However, these studies do not take into account that in essence, it is not all stocks that actually earn positive (negative) abnormal returns as expected after the rating revision is made. It is possible that the documented significant reaction to new buys and new sells in aggregate is due to the significant out (under) performance of just a few stocks, in which case it is not necessarily correct to generalise the results to include all the stocks. Arguably, there is mileage in investigating whether all stocks that receive buy (sell) recommendation perform as expected. One of the aims of the current study is to investigate the reasons for non-conformance by some new buy and new sell stocks regardless of overall performance.

2.2.4.2 *Stock rating systems*

Until recently, different analysts used different rating systems for their recommendations. Typically, they used terms such as strong buy, buy, near term or long term accumulate, near term or long term over/out-perform or underperform, neutral, hold, reduce, sell and strong sell. Ho and Harris (1998) indicate that one of the reasons for having more rating categories than just three (buy, sell, hold) was to provide an opportunity to sugar-coat bad news and/or to send more subtle signals. For example, in a five level system, a recommendation downgraded to "underperform" may be substituted for a harsher change to the bottom category of "sell". This suggests that additional rating categories were used to avoid the harsh statement of negative news.

Some studies such as Stickel (1995), Womack (1996), Ryan and Taffler (2005) and Laderman (1998) recognise that upgrades of stocks are more common than downgrades with only 1% or less of all recommendations made by analysts being new "sells". This is why Dorfman (1996) goes as far as suggesting that investors have developed a belief that the "hold" recommendation is another way of recommending "sell". The disparity between the number of analysts' "buy" and "sell" recommendations was interpreted as evidence that analysts' objectivity and independence are compromised. Analysts had to compromise because issuing negative recommendations would deny them access to management (Chen and Matsumoto, 2003)

The pattern in the distribution of buy and sell recommendations has changed since the implementation of NASD 2711 and SEC rule 472. Madureira (2004) observes that the proportion of sells now exceeds the proportion of buys and he attributes this drastic change in the distribution of stock recommendations to the disclosure requirements of NASD 2711. The change in the distribution of stock recommendations is accompanied by a more clear and easy to understand rating system because of Rule 472 which requires that the definition of ratings should be the same as their meaning. Madureira (2004) confirms that seven of the ten large brokerage firms that were involved in the Global Settlement have adopted the new rating system. This suggests that the blur caused by the rating systems used by different brokerage firms may soon disappear.

2.2.4.3 *Characteristics of stocks that receive the most optimistic rating*

Some studies investigate the characteristics of stocks that receive optimistic rating. Jegadeesh et al., (2004) indicate that analysts prefer high momentum stocks and growth stocks. Thus, stocks that receive buy ratings typically have more positive price momentum, higher trading volume, higher past and projected growth, more positive accounting accruals and more aggressive capital expenditure. Stickel (2000) supports the findings of Jegadeesh et al., (2004) by showing that Wall Street darlings who are awarded buy recommendations have recent positive EPS momentum and surprise, recent positive relative price momentum, and recent positive EPS forecast revisions. Bradshaw (2002) and Bradshaw (2004) suggest that analysts prefer the price-earnings-to-growth model and long-term growth when they value stocks and do not use present

value models as would be expected. He argues that buy-and-hold investors would earn higher returns when relying on present value models that incorporate analysts' earnings forecasts than on analysts' stock recommendations. Asquith et al., (2005) show that the three methodologies used to value stock generally fall into three categories; earnings or cash flow multiples, discounted cash flow (DCF) and asset multiples. However, they find that the market does not react differently depending on the valuation methodology used by the analyst or whether the analyst uses one or many.

These studies suggest that stock characteristics tend to determine the type of rating awarded on them. The drawback of these studies, however, is that they put most emphasis on the stocks that receive buy ratings and say little, if anything, about stocks that receive sell ratings. Furthermore, these studies do not take into account the fact that not all stocks that are awarded buy ratings perform as expected subsequently. The current study is similar to these studies in that it assumes that stock characteristics may explain some stock ratings issued by analysts. The difference is that the current study includes other non-stock characteristics in its models and concentrates on both new buy and new sell recommendations that lack market impact. In addition, it concentrates on the potential cognitive and behavioural biases analysts may be subject to in their judgements, which is a perspective original to the literature.

2.2.5 Analysts' conflicts of interest

Until recently, brokerage firms have been spending huge amounts of money on analysts to analyse stocks and make investment recommendations. However, as indicated above, research casts doubt on whether investors can benefit from following their recommendations *inter alia*, because of the alleged conflicts of interest between brokerage firms and their clients which tainted analysts' objectivity and independence. Michaely and Womack (1999) document that investment banks traditionally have three sources of income: (1) corporate financing and the issuance of securities and merger advisory services, (2) brokerage services, and (3) proprietary trading. These three income sources may have created conflicts of interest within the bank and with its clients. In fact, frequent conflicts appeared to occur between a bank's corporate finance arm and its brokerage operation. The corporate finance division of the bank is

responsible for completing transactions such as initial public offerings (IPOs), seasoned equity offerings, and promoting mergers by new and current clients. The brokerage operation and its equity research department, on the other hand, were motivated to maximise commissions and spreads by providing timely, high quality information. These two objectives may conflict. These conflicts of interest clearly had a negative impact on investor perceptions of the reliability of analyst recommendations and Reg FD) could have attempted to stop this by, in effect, seeking to separate investment banking from equity research.

Dugar and Nathan (1995) and Michaely and Womack (1999) show that market participants seem to be aware of the effect of investment banking relationships on analysts' incentives and discount the optimism in investment banker analyst research reports more heavily. Lin and McNichols (1998) document that affiliated analysts do issue overly favourable recommendations to maintain client relationships and investors expect lead analysts to recommend "hold" when "sell" is warranted. Hirst et al., (1995) show that investors do distinguish between analysts with differential incentives, however, investors only incorporate such differential incentives into their stock performance models when the analyst report is unfavourable.

A number of studies have been conducted after the implementation of rules and regulations (see section 2.2.6 below) meant to govern brokerage firms and analysts. The main aim of most of these studies is to determine whether overly optimistic analysts' research reports were a result of analysts' conflicts of interest as alleged in the Global Settlement (see section 2.2.6.3 below) and if analysts' behaviour has changed after the regulatory intervention. Barber et al., (2004) find that abnormal returns from the buy recommendations issued by independent firms exceed those from the investment banks and suggest that at least part of the underperformance in the buy recommendations issued by the investment banks is in line with biased research by investment banks. Cliff (2004) and Agrawal and Chen (2005) draw the same conclusion as Barber et al., (2004). However, they go further and show that the reasons for underwriting firms' poor performance are due to conflicts of interest and selection bias. However, Cliff (2004) acknowledges that "there is probably more to the story than that" (p. 25) suggesting that

there may be other factors to explain why analysts issue particular recommendations on stocks while Agrawal and Chen (2005) conclude that investors are sophisticated enough to adjust for analysts' bias.

Other studies do not find conflicts of interest in analysts' recommendations, when comparing analysts' recommendations before and after the implementation of rules, while still others conclude that even if there were conflicts of interest, their magnitude does not warrant the Global Settlement. I believe that any study that shows that there is no conflict of interest in analysts' recommendations or that conflicts of interest do not explain the level of excessive optimism in analysts' research reports suggests that the effectiveness of rules set up to govern analysts by policy-makers to date to restrain overly optimistic analysts' recommendations may have a limited effect.

Chan et al., (2004) find that brokerage firms trade on their recommendations. Their results are inconsistent with the reasons for the Global Settlement (see section 2.2.6.3). However, they explain their results further by showing that it may just be that firms provide a public show of solidarity to their analysts by trading on their recommendations. Bajari and Krainer (2004) find that the magnitude of the effects of conflicts of interest on recommendations appears to be too small. They document that the main factors influencing stock recommendations are publicly observable information and peer group, as opposed to conflicts of interest arising from the relationships between companies and brokerage firms. Iskoz (2003) finds differences in performance of affiliated and unaffiliated brokerage firms on IPOs only for strong buys while Kolasinski and Kothari (2004) conclude that the cause of overly positive recommendations has more to do with execution-related conflicts of interest or selection bias but with by incentives derived from investment banking business.

Gallant (1990), Boni and Womack (2001), Ho and Harris (1998) and Francis and Philbrick (1993) observe that the majority of analysts' reports were positive because companies would limit the analyst's access to their companies if a "sell" recommendation is made for their stock, making it difficult for them to obtain the company specific information they need for their analysis. After all, in most cases, it is

the company that has control of the disclosure process and therefore on how much information to divulge.

The lack of objectivity on the part of analysts was exacerbated by their compensation structure. Although analysts are professionals who want to build and maintain their credibility, they were obviously torn between promoting the best investment advice and thereby a good reputation. For that reason, their compensation was not necessarily based on the quality of their research or stock recommendation success over time. Until recently, analyst compensation packages generally consisted of base salary, a percentage of the investment banking deals in which they were involved and a percentage of the trading volume generated by their research coverage. With this arrangement, it was possible for analysts to lose objectivity in stock coverage decisions and earnings forecasts. Hong and Kubik (2003) explain analysts' bias by pointing to the reward system used by brokerage firms. Their findings imply that analysts who are optimistic are much less likely to be fired from the top brokerage firms, and are much more likely to be promoted or hired by a more high-powered house. The study also finds that analysts are judged less on accuracy when it comes to stocks underwritten by their houses. Chan et al., (2002) look into analysts' conflicts of interest and biases in earnings forecasts and conclude that earnings forecast bias is exacerbated by the fact that investors handsomely reward stocks that achieve runs of non-negative surprises. Rule 472 addresses the compensation structure issue and it is anticipated that objectivity problems arising from brokerage firms' compensation structure will be somewhat kept at bay as a result.

As can be seen above, results of the studies on analysts' conflicts of interest are mixed. Some studies document that analysts are influenced by conflicts of interest while others conclude that potential conflicts of interest do not fully explain the levels of optimism in analysts' recommendations. The difficulty with these studies is that from the onset they assume that the problem of analysts' optimistic recommendations is mainly caused by the analysts' conflicts of interest, and as a result do not incorporate within the studies many other factors that may be just as important in influencing stock recommendations. The current study assumes that there are many other factors influencing analysts'

recommendations other than their conflicts of interest. Being able to identify more important factors that influence analysts' stock recommendations is essential in terms of developing a more robust model that can predict analysts' stock recommendations. The other drawback of these studies is that they put less emphasis on sell recommendations and concentrate entirely on the buy recommendations. I believe that to have a complete picture of stock recommendations and the factors underlying them, both buy and sell recommendations should be analysed concurrently.

2.2.6   Regulation of financial analysts

In order to address the concern about financial analysts' conflicts of interest, the SEC and other regulatory agencies have introduced rules and regulations to govern equity research as well as the relationship between brokerage firms and financial analysts. The following subsections discuss some of these regulations and the findings and conclusions of the studies that have investigated their efficacy to date.

2.2.6.1   Regulation Fair Disclosure (Reg FD)

The Regulation Fair Disclosure (Reg FD) was implemented on October 23rd, 2000. This regulation provides that companies should not disclose material information only to selected individuals but should make public disclosure of that information. Reg FD is actually meant to curb the practice where top executives in the companies would disclose information to certain analysts, often to those analysts with whom they have an investment banking relationship.

Various studies have investigated the effectiveness of Reg FD. Some of these studies conclude that Reg FD has achieved the intended objectives while others conclude it has unintended effects. Gintschel and Markov (2004) find that the price impact of earnings forecasts and stock recommendations is lower following the implementation of Reg FD and they conclude that this is because analysts no longer have access to private information regarding earnings as well as other information relevant for their stock valuation task. Their findings thus suggest that Reg FD is effective. Mohanram and Sunder (2003) conclude that Reg FD has resulted in analysts' increased independence from management. Interestingly, they also find that analysts who were classified as stars

pre Reg FD are not maintaining their edge post Reg FD. Their findings suggest that before the implementation of Reg FD, relationships with management mattered more than hard work. Other studies such as Ahmed and Schneible (2005), Chen and Matsumoto (2003) and Heflin et al., (2003) also provide evidence to support the efficacy of Reg FD.

However, other studies do not support the SEC and other agencies' concern that analyst research is highly dependent on information from management. Ke and Yu (2005) do not find evidence that the informativeness of analysts' stock recommendations is due to their privileged access to management's private information. Chen and Marquez (2003) focused on the effect of strengthened "Chinese Walls" and mandatory disclosure on analyst compensation. They conclude that information barriers due to strengthened "Chinese Walls" can increase research efforts and improve quality. However, they also point out that this type of regulation can also reduce information production and lower the quality of reports if a brokerage firm derives intrinsic benefit from its analyst research activity. Their results suggest that some provisions of Reg FD are effective while others may have unintended effects.

2.2.6.2 Regulations NASD 2711 and NYSE 472

NASD 2711, *Research Analysts and Research Reports* and NYSE's amendment to its Rule 472, *Communication with the Public* were effected around the same time, on the 9th July, 2002. Although both rules are titled differently, they have identical requirements. They both require that analyst research reports display the proportion of issuing firm's recommendations that are buys, holds and sells.

Few studies have investigated the efficacy of NASD 2711 and Rule 472 to date. Barber et al., (2004) observe that from mid 2000, the percentage of buys decreased steadily and by the end of June 2003, buys exceeded sells by less than a 3-1 ratio. They conclude that although the results may be a consequence of the economic downturn that occurred during the sample period, there is strong evidence that the results are due to the influence of NASD 2711 which requires brokers' ratings distributions to be made public. Madureira (2004) also attests that these rules are effective in terms of the

distribution of stock recommendation ratings. He also points out that the important shift starts with the adoption of new rating systems by some of the top brokerage firms, which is in line with the requirements of Rule 472. One of the clauses of Rule 472 states that definition of rating terms should be in line with their meaning.

2.2.6.3 Global Analyst Research Settlement

In April 2003, a settlement commonly known as the "Global Analyst Research Settlement" was reached between the top ten US brokerage firms and the SEC, NYSE, NASD and the New York Attorney General. According to the settlement, the top ten brokerage firms had to pay penalties for the alleged misconduct that resulted in investors losing huge amounts of money from trading on their analysts' stock recommendations. In addition to the penalties, they also had to pay to fund independent research and seven of the brokerage firms had to pay further to fund and promote investor relations. In addition to monetary penalties, all brokerage firms were also required to make changes in their businesses including cutting off equity research from investment banking by strengthening the "Chinese Walls" between the two.

Some studies have looked into the effectiveness of the Global Settlement. Kadan et al., (2004) find that affiliated recommendations are still more optimistic than unaffiliated recommendations but the differential optimism is significantly lower after the implementation of the Global Settlement. On this basis, they conclude the Global Settlement is effective and any other remaining bias found with affiliated analysts can be attributed to selection bias. Madureira (2004) finds evidence of an overall change in the distribution of recommendations issued by the top 10 brokerage firms after the Global Settlement, with them leaning towards less optimistic ratings.

The mixed results found to date regarding financial analysts' conflicts of interest and the efficacy of the rules governing equity research serve to show that the problem of optimism in analysts' recommendations may not be entirely a problem of relationship between brokerage firms and companies, but may be a problem instigated by conflicts of interest and other important issues. As mentioned earlier, the current study addresses

the factors that influence analysts' recommendations by taking into account the potential conflicts of interest, analysts' psychological biases and other key factors.

To summarise this section, one of the most important analysts' outputs is their stock recommendations. Research has found that, contrary to what an average investor may expect, analysts do not use information contained in companies' financial reports appropriately in valuing the stocks they cover, but rely largely on soft, qualitative information provided outside of company reports. The latter may be influenced by several factors including the relationship that the analysts' investment banks have with the companies whose stock they cover and analysts' psychological biases. The underlying thesis of this research is that the factors which affect analysts at the time they gather, process and interpret information, may broadly account for the observed lack of market impact of analysts' recommendations.

2.3   Analysts' behaviour and market anomalies

Like any other human beings, analysts are prone to errors in their work. The insights of behavioural finance, which is a comparatively new finance discipline using psychology to better understand the behaviour of investors and other market participants, may well be helpful in explaining such analyst biases. The purpose of this study is to seek to understand how psychological biases, together with other market factors, may jointly influence analysts to issue stock recommendations that lack market impact.

2.3.1   Financial analysts and market anomalies

The efficient market hypothesis (EMH) states that when markets are efficient, stock prices "fully reflect all publicly available information". This means that investors will "pounce" on any new information that may have a bearing on stock prices, swiftly driving share prices up or down. According to the EMH, stock prices are unbiased estimates of fundamental value. This implies that financial analysts are unable to earn returns sufficient to compensate for their costs and still earn an economic profit. Rapid price movements due to new information cause randomness in successive price changes.

The EMH is based on the assumption that investors are rational and consider all available information in their decision-making processes. But if the market is efficient, what role then do analysts play and how are they compensated? Research shows that too often investors (analysts) are irrational (e.g., Shefrin and Statman, 1995; Barber and Odean, 2001 and DeBondt and Thaler, 1985). Also, there are some securities that do not reflect all public information (weakly efficient) implying that investors may be able to make use of this inefficiency to earn abnormal profits (e.g., Keim, 1983).

There are evident inefficiencies (anomalies) that appear to contradict the EMH, both at the market-wide and individual security level. These anomalies suggest that the principles of rational behaviour underlying the efficient market hypothesis are not entirely correct. This implies that I need to look at models of human behaviour as well to understand such anomalies.

At the market-wide level Jegadeesh and Titman (1993) show that trading strategies that buy past winners and sell past losers realise significant abnormal returns (stocks exhibit a momentum property). Lo and MacKinlay (1988) find positive serial correlation for a diversified portfolio of shares. Fama and French (1988) confirm excess volatility claims by showing that returns tend to be negatively autocorrelated over horizons of three to five years. Campbell and Shiller (1988) show that the earnings yield can help predict share prices. DeBondt and Thaler (1985) find evidence of long-term stock price overreaction and negative serial correlation for individual stocks.

Different studies have also documented firm specific anomalies. Banz (1981) and Reinganum (1982) show that small companies earn higher rates of return than large companies stocks. Keim (1983) finds that abnormal returns from February to December inclusive tend to be similar but small firms experience a positive January effect while large firms experience a negative January effect. Fama and French (1992); Lakonishok et al., (1994) and Loughran (1997) find that the book-to- market ratio can predict returns on securities.

There are different explanations put forward for these anomalies. Conrad and Kaul (1993) suggest that the anomalies are due to statistical measurement errors. Fama and French (1996) argue that the observed difference between returns on value and growth portfolios mirror a compensation for bearing risk. Fama (1998) further documents that long-term return anomalies are sensitive to methodology and the overreaction and underreaction that are observed in the financial markets are evidence that anomalies from the standpoint of the EMH are just "chance results". Jagannathan and Wang (1996) document that when human capital and the business cycle are included in the CAPM, firm size and book-to-market anomalies drop out.

Other studies attribute the anomalies to psychological errors made by analysts. DeBondt and Thaler (1985) find that stocks that have been losers over a period of two to five years go on to subsequently yield higher rates of return than the corresponding prior winner stocks. They attribute the long-term return reversal to investor overreaction. DeBondt and Thaler (1990) argue that analysts have a tendency to overreact and form expectations that are too extreme. Abarbanell and Bernard (1992) and Klein (1990) indicate that analysts' forecasts appear to underreact to information in past quarterly earnings and past quarterly returns, which may imply that analysts are responsible for anomalies via their forecast errors. Eastwood and Nutt (1999) demonstrate that in fact analysts underreact to negative earnings news but overreact to positive news and therefore appear systematically optimistic. Tamura (2002) interprets his results as evidence that financial analysts systematically underreact to publicly available information and fail to make rational forecasts. In the latest study, Pinsker (2005) investigates the effect of Reg FD. Using laboratory experiments, he argues that Reg FD requires firms to disclose information sequentially to the market as opposed to multiple material events pre Reg FD. He shows that sequential disclosure increases volatility and variation in stock price beliefs among investors which is in line with the explanation that investors overreact to sequential information. He concludes that Reg FD may not achieve its intended goals.

Although Fama (1998) posits that the overreaction and underreaction that are observed in the financial markets are just "chance results", Barberis et al., (1998) provide a

psychological model which tries to reconcile the overreaction and underreaction evidence from the financial markets. Other studies such as those of Daniel et al., (1998) and Wang (2001) formulate other psychological models.

2.3.2   Analysts and cognitive biases

The apparent errors made by analysts can best be explained by behavioural finance concepts which seek to use psychology to explain the decision-making process of the investor. Olsen (1998) asserts that behavioural finance does not try to define "rational" behaviour or label decision-making as faulty; but it seeks to predict systematic financial markets implications of psychological decision processes. Behavioural finance is based, *inter alia*, on the work of Tversky and Kahneman (1974) who show that when people are faced with complicated judgements or decisions, they simplify the task by relying on heuristics and general rules of thumb. In many cases, these short cuts yield very close approximations to the "optimal" answers suggested by normative theories. The advantage of heuristics is that they reduce the time and effort required to make reasonably good judgements and decisions. Although there are various cognitive biases documented in the psychological literature, the two salient biases recognised in the literature as key in explaining the "irrational" behaviour of market participants are overconfidence and representativeness. I concentrate on their potential impact in explaining analyst behaviour in this study.

2.3.2.1   Overconfidence

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

demands, risk management and tax consequences are taken into consideration. He suggests that this behaviour of selling winners too soon is motivated by overconfidence.

Barber and Odean (2001) assert that rational investors trade only if the expected gains exceed transaction costs. But overconfident investors overestimate the precision of their information and thereby the expected gain of trading. They also observe that since men are more confident than women are, men will trade more and perform worse than women. Odean (1998b) concludes that overconfidence is costly to society and that overconfident traders do not share risk optimally. Overconfidence increases trading volume and market depth but decreases the expected utility of overconfident traders. Gervais and Odean (2001) describe both the process by which traders learn about their abilities and how a bias in this learning can create overconfident traders. They conclude that in assessing his ability, the trader takes too much credit for his success and as a result becomes overconfident. Massey and Thaler (2005) analyse the decision-making of National Football League teams during the annual player draft. They conclude that the task of picking players is an extremely difficult one and it is extremely difficult to avoid overconfidence in this task. The more information teams acquire about players, the more overconfident they will feel about their ability to make fine distinctions, the "illusion of knowledge".

2.3.2.2 Representativeness

The representativeness heuristic (Tversky and Kahneman, 1974) involves making judgements based on stereotypes rather than on the underlying characteristics of the decision task. People tend to try and categorise events as typical of a representative of a well-known class and then in making probability estimates that overstress the importance of such a categorisation, disregard evidence about the underlying probabilities. One consequence of this heuristic is for people to see patterns in data that is truly random and draw conclusions based on very little information. Shefrin and Statman (1995) indicate that investors believe that good stocks are stocks of good companies, which is not necessarily true. This is rooted in the representative bias, which supports the idea that winners will always be winners and losers will always be losers. Solt and Statman (1989) actually observe that, in effect, stocks of good companies tend

to be outperformed by stocks of bad companies. This is because investors attach higher expected returns to stocks that have experienced previous higher sales growth. DeBondt and Thaler (1985) argue that because investors rely on the representative heuristic they could become overly optimistic about past winners and overly pessimistic about past losers. This bias could cause prices to deviate from their fundamental level.

Although very interesting methodologies have been used in various studies to document investors' overconfidence and representativeness bias, none has linked the words, particularly the tone of language that analysts use to justify their recommendations to their psychological biases. Because it is difficult to directly measure psychological drivers of analyst judgements, various studies have attempted to understand their psychological behaviour by using their stock recommendations, earnings forecast and other numerical information they produce. Little, if any, attempt has been made to link analysts' textual data, found in the reports that they prepare to justify their stock recommendation, to the potential psychological biases to which they might be prone.

To summarise this section, analyst psychological biases such as overconfidence and representativeness may explain some of the anomalies observed in the financial markets. Overconfidence bias arises if an analyst overestimates what he/she can do compared to his/her abilities while the representativeness bias arises when an analyst unconsciously relies on stereotypes in making decisions on the stocks that he/she follows.

2.4 Conceptual framework

The aim of this section is to integrate the two strands of literature from section 2.2 and section 2.3 above to build a conceptual framework which identifies those factors potentially influencing financial analysts' stock recommendations.

Box 1 of the framework shows that the niche of my research is analysts' stock recommendations. My initial proposition is that analyst's stock recommendations,

Analysts' recommendation drivers

Market dimensions

Overconfidence bias
Optimism
Certainty

Representativeness bias
Activity
Momentum
Firm size
Book-to-market
Target price change

Other factors
Investment relationships

Corporate information

Control variable
Analysts' following
(6)

Analysts' stock recommend ations (1)

Lack of market impact (2)

Why? (3)

The market is efficient? (4)

Analysts are biased? (5)

Underlying research theme
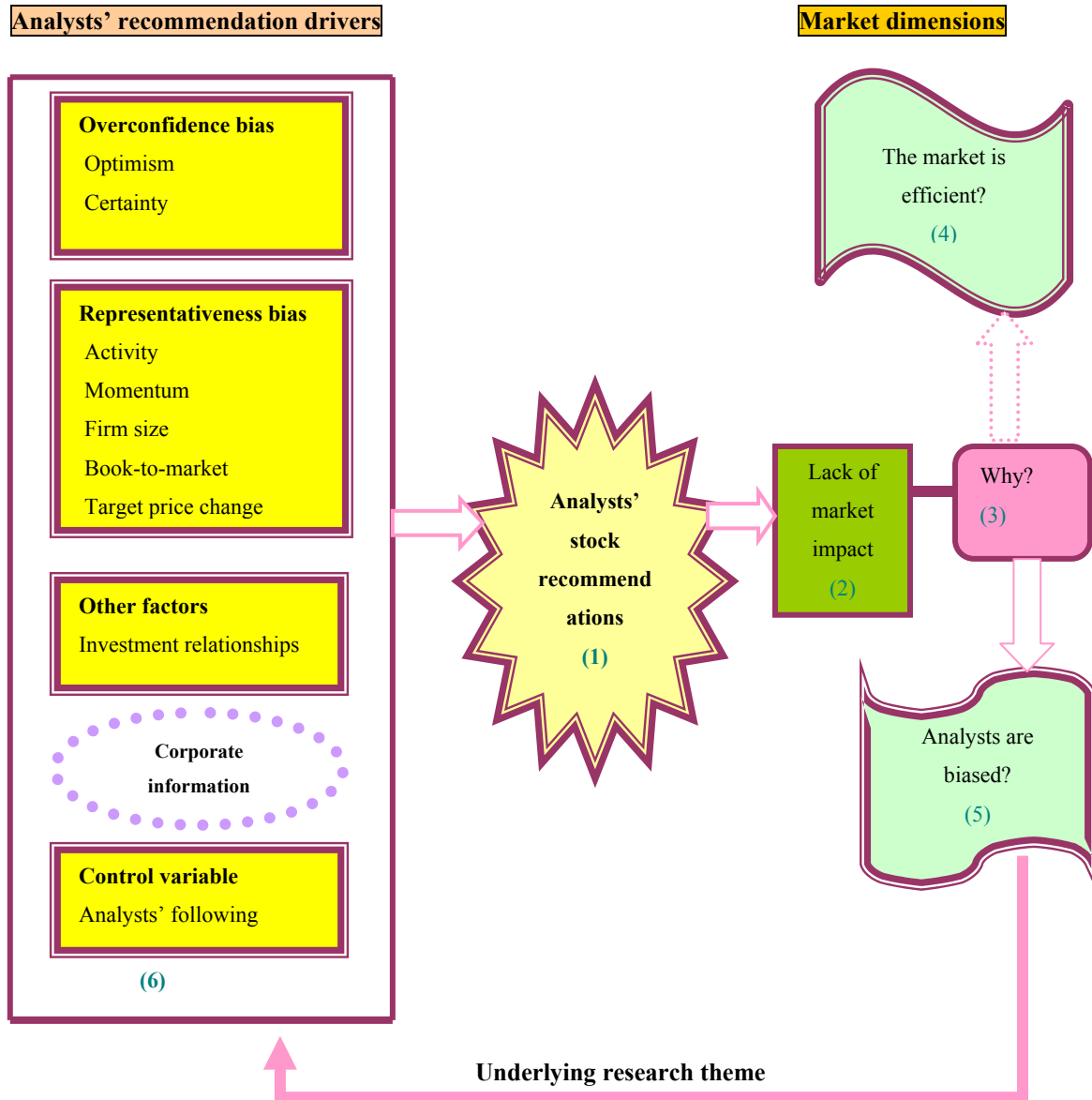
which are the integral output from analysts' work, lack market impact (box 2). Market impact is defined in this study as the unexpected performance after a stock recommendation is changed from one category to another. For instance, if a recommendation is changed to a buy category and, over the twelve months period after the recommendation is changed, the stock earns an insignificant or negative abnormal

return contrary to the expected positive return, then that new buy recommendation is assumed to lack market impact. Similarly, if a new sell recommendation accrues positive or minimal abnormal returns, not the expected negative return, over the twelve months period after the recommendation is changed, this sell signal is assumed to lack market impact.

The logic following my proposition is to ask why do analyst stock recommendations perform contrary to the expectations (box 3). The established lack of market impact of analyst recommendations could be due to the following alternative hypotheses, the market is efficient (box 4) or that analysts are "biased" and therefore "inefficient" (box 5). I reject efficient market theory (box 4), because I assume that in theory, if analysts do their job properly using all relevant information, including the insider information which they used to have privilege of, then their recommendations would have measurable market impact. Until very recently, much of the information analysts used was gathered from companies themselves through company visits, analysts' meetings, results announcements and other means (Barker, 1998).

The key Efficient Market Hypotheses (EMH) focuses on the market reaction to new price sensitive information. Therefore, I propose in this thesis that the lack of market reaction to most analysts' recommendations is consistent with an alternative explanation (box 5) that their recommendations have little market value/information content as a result of the manner in which judgements and recommendations are made and the factors driving these (box 6).

My conceptual framework categorises these 'driving factors' into overconfidence bias and representativeness bias and further shows analyst following as a control factor (box 6). Overconfidence bias is measured by *Diction* variable optimism and certainty. Representativeness bias is measured by *Diction* variable activity.[1] Other factors that serve as measures of representativeness bias are, previous price performance of the stock (momentum), firm size, book-to-market, and target prices. The relationships

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[1] Refer to chapter 4, section 4.4 for information on how the content analysis using *Diction* software is conducted.

between the brokerage firms and companies (investment-relations) and number of analysts following the firm are used as control variables. (See chapter 3 for a complete description of these factors).

2.5   *Summary, research gaps and research questions*

The stock recommendations issued by financial analysts are an issue of concern to both investors and policy-makers alike. This chapter reviews evidence on (1) the type of data that analysts use to form an opinion about the future value of the firm on which they are commenting, (2) whether their stock recommendations have economic value, (3) analysts conflicts' of interest and the regulations put into place to curb these, and (4) the role of analysts in the documented market anomalies as well as the cognitive biases that analysts may resort to in order to cope with the complexity of their tasks. Based on this evidence, I am able to identify the gaps in the extant literature and where the current study can be able to make significant contribution.

The gaps in the literature are identified as follows: First, an important gap in the extant finance literature resides with the type of information that analysts use to justify their recommendations. For example, Rogers and Grant (1997) assert that financial reports provide 52% of the information cited by analysts and 48% is external to the financial reporting process. In effect, this strand of literature alludes to the fact that the information that analysts actually use differs from their justification for their recommendations. In this study, I attempt to investigate where the information that is not explained by firms' financial reports comes from.

Second, various studies show that these recommendations have negligible effect on the market. Barber et al., (2001) document that trading on security analysts' recommendations would not yield the investor positive abnormal returns. They build hypothetical portfolios containing the most favourable consensus stock recommendations on each day. They find that these portfolios do earn above average returns but only before taking into account transaction costs and risk. After accounting for these, investors do not earn better than average returns. Womack (1996) and Ryan and Taffler (2005), on the other hand, find that stocks following new "buy"

recommendations continue to go up for four to six weeks after the new stock recommendation was made while "sell" recommendations drift lower for six more months. Their results suggest that the average level of recommendation has little investment value but changes in levels are valuable although for a limited time. Ryan and Taffler (2005) find that only new "sells" and recommendations for smaller less followed stocks have investment value. However, these studies do not attempt to explain what could be the reasons for the general lack of impact of stock recommendations on the market.

Third, studies that document the psychological biases that analysts might be prone to investigate how stocks react to their recommendations (see Barberis et al., 1998; Daniel et al., 1998 and DeBondt and Thaler, 1985) but fail to trace directly the existence of judgemental bias in the way that analysts prepare their reports. My empirical findings should be able to explain better what the actual role of analysts in the financial market was and is.

Having identified these research gaps, my research question is framed as follows:
What factors influence analysts at the time that they gather, process and interpret information on stocks so that they eventually issue stock recommendations that lack market impact?

- Is it conceivable that analysts make errors in their recommendations because their decisions are highly influenced by psychological bias?

- Is it plausible that the analysts' role in corporate finance and other activities is driving their recommendations, given that Michaely and Womack (1999) and Dugar and Nathan (1995) suggest that analysts employed by brokerage firms who also have underwriting relationships with the company they follow have the economic incentives to issue more favourable recommendations?

- Is it possible that the characteristics of stocks as outlined by Stickel (2000) and Jegadeesh et al., (2004), and not the quantitative information from companies' reports, are the sole determinants of the type of recommendations that analysts issue?

- Studies, such as those of Brav and Lehavy (2003) document that target prices have market impact both conditional and unconditional to the presence of stock recommendations. However, it is not quite clear what the role of target prices that are issued concurrent with stock recommendations is. Is it possible that stock recommendations drive stock recommendations and that target prices that are issued concurrent with stock recommendations are only meant to peddle analysts' optimistic recommendations as suggested by Asquith et al., (2005)?

To address these research questions, in chapter 7 I evaluate the performance of stocks that are awarded new buy and new sell recommendations and then select the stocks that perform contrary to the expectations. The testable hypotheses about the reasons for these stocks' lack of market impact are developed in the next chapter (Chapter 3) and tested in Chapter 8.

Chapter 3 Hypotheses development and variables

3.1 Introduction

The previous chapter concluded by providing the conceptual model used in this study together with the research gaps and research questions from the literature. The purpose of this chapter is to develop testable hypotheses derived from the conceptual framework in Figure 1 section 2.4 and from the extant literature in order to address the gaps identified in the literature and to answer the research questions specified in chapter 2. Because the essence of this research is to assess the impact of psychological biases on nonconforming analysts' recommendations, the hypotheses to be tested are mainly about psychological biases. Thus, my first null hypothesis relates to overconfidence bias while the next five null hypotheses relate mainly to representativeness bias. My last null hypothesis test for the effect of existing corporate relationships between investment banks and firms on the type of stock recommendations that analysts issue. I also state my control variable and how it is derived from the literature.

The chapter is organised as follows. Section 3.2 describes the hypotheses to be tested and associated proxy variables. Section 3.3 provides the rationale for a control variable used and how this control variable is derived from the literature. Section 3.4 concludes the chapter.

3.2 Hypothesis development and variables

3.2.1 Do overconfidence and representativeness biases influence analysts' decisions about the stock recommendations they issue?

Tversky and Kahneman (1974) postulate that when people are faced with complicated judgements or decisions, they simplify the task by relying on heuristics or general rules of thumb. The advantage of heuristics/cues is that they reduce the time and effort required to make reasonably good judgements and decisions. Because of the complex nature of analysts' work, I postulate they are likely to be prone to cognitive biases, in particular, they are prone to overconfidence and representativeness biases.

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Cognitive biases are very difficult to measure outside the abstracted situation of a psychological laboratory. However, in this research, analysts' cognitive thinking is inferred, *inter alia,* from the tone of language they use when they prepare their research reports. When analysts change a stock recommendation from one category to another, they normally prepare research reports. Most research reports contain a new or a reiterated stock rating as well as other information pertaining to the company, such as target price, earnings forecast, segment data, affiliation, valuation models (Asquith et al., 2005) and industry data. But, most importantly, there is textual information providing the analysts' justification for the type of stock rating granted. It is the tone of language that analysts use to justify their recommendation that helps us to infer their thinking at the time that they prepare their reports.

The overconfidence bias in the tone of language that analysts use is measured by *Diction* variables OPTIMISM and CERTAINTY. OPTIMISM is defined in *Diction* as language endorsing some person, group, concept or event or highlighting their positive entailment while CERTAINTY is defined as language indicating resoluteness, inflexibility, completeness and a tendency to speak *ex cathedra*. If analysts' overconfidence bias (as measured by OPTIMISM and CERTAINTY) influences the decision they make about stocks, then I expect it to have a positive (negative) significant impact on the buy (sell) recommendations which lack impact. The null hypotheses 1 is therefore established as follows:

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

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

H2₀: The tone of the language used by the investment analysts in their research reports to justify the stock ratings is not positively biased towards the level of activity (or change) taking place within the company

A complete overview of the methodology used to measure these cognitive biases is shown in chapter 4, section 4.5.

3.2.2 Does the previous price performance influence the type of rating financial analysts award to the stocks they follow?

A consistent increase in the stock price from one reporting period to another is an indication of momentum in stock price. Momentum is a well known phenomenon in finance. For example, Jegadeesh and Titman (1993) show that past winners outperform past losers over the 3-12 months' time horizon, thus exhibiting the property of momentum. On the other hand Jegadeesh et al., (2004) show that analysts prefer "glamour" stocks which, among others, exhibit high price momentum.

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

H3₀: The coefficient of price momentum is negative (positive) and insignificant in predicting that analysts will issue a buy (sell) recommendation which does not perform as expected.

A variable called PRICE_MOM is used to capture the effect of price momentum on the explanation of buy/sell recommendations. Because a stock's past performance may have a direct influence on the type of stock recommendation that an analyst issues, it is

expected that the coefficient of PRICE_MOM will be positive for buy recommendations and negative for sell recommendations. That is, firms that receive buy recommendations are those that have consistently performed well in the recent past (positive sign), while sell recommendations are given to stocks that have not performed well over the previous period (negative sign)

3.2.3 *Does firm size influence the type of rating financial analysts award to the stocks they follow?*

The relationship between firm size and stock returns is well documented in the finance literature (e.g., Banz, 1981; Reinganum, 1982; Keim, 1983). Fama and French (1992) identify firm size as one of the factors that have a significant relation to stock returns. Stickel (1995) documents the firm size effect for buy and sell recommendations by finding that smaller firms have a larger reaction to Value Line rank changes.

I consider firm size as another form of representativeness bias in that analysts assume that the size of the firm in terms of its market capitalisation is representative of its future performance, i.e., the larger the firm the better its going to perform in the future. The null hypothesis 4 is therefore established as follows:

$H4_0$:   The size of the firm does not have any significant impact on the type of stock recommendation that analysts issue on the stock.

A variable FIRM_SIZE is used to pick up the effect of firm size in the determination of buy and sell recommendations. My conjecture is that large firms are less likely to receive sell recommendations than small firms. As in Mikhail et al., (2004), the size of the firm is measured using the natural logarithm of the market value of equity for the firm at the end of the financial year preceding the recommendation revision. The coefficient on FIRM_SIZE is expected to be positive for buy recommendations and negative for sell recommendations. Thus, large firms will have a positive influence on the stock recommendation.

3.2.4 Does book-to-market influence the type of rating that financial analysts award to the stocks they follow?

The book-to-market effect, together with the explanation for the effect, is well documented in the literature. Fama and French (1992) find that book-to-market has a significant relation to stock returns. Fama and French (1993 and 1996) interpret the return to book-to-market as compensation for state dependent risk related to relative financial distress. However, Skinner and Sloan (1999) argue that the distress factor results from mispricing.

Most buy recommendations are made by analysts who tend to favour "growth" compared to "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., 2001). Based on this literature, I expect that stocks which have low book-to-market ratios (growth stocks) are more likely to receive buy recommendations than stocks with high book-to-market (value stocks). Book-to-market is yet another form of representativeness bias because the development stage of the firm is regarded as representative of the stock's future performance by analysts. The null hypothesis 5 is therefore established as follows:

$H5_0$: **The firm's book-to-market does not have any significant impact on the type of stock recommendation that analysts issue on the stock**.

A variable BTOM is used to capture the effect of book-to-market on the nonconforming stock recommendations. It is measured as book value per share divided by market value of equity. Book value per share is calculated as total assets minus total liabilities deflated by common shares outstanding at the end of the firm's previous fiscal year. Market value of equity is calculated by multiplying firms' market value by the total number of shares in issue (Mikhail et al., 2004). All accounting variables are obtained

from *Compustat*. The coefficient of BTOM is expected to be positive for buy recommendations and negative for sell recommendations.

3.2.5 *Does target price influence the type of rating financial analysts award to the stocks they follow?*

Buy and sell recommendations that are changed from one category to another are often issued together with other information such as target prices. Bradshaw (2002) points out that target prices serve to justify the recommendation in the analyst report. However, target prices are not always issued to justify recommendations, but as an independent means of informing investors about stock value. Brav and Lehavy (2003) show that target prices are perceived as being more informative signals regarding a firm's value, whether issued with or without stock recommendations.

Some researchers have doubted whether target prices provide any information over and above information in stock recommendations (Michaely and Womack, 2003). However, Brav and Lehavy (2003) document a significant market reaction to a change in target prices, both unconditionally and conditional on contemporaneously issued stock recommendation and earnings forecast revisions. Their results suggest that price targets have information content beyond what is contained in stock recommendations. As such, stock recommendations should not be looked at in isolation by investors but should be used together with target prices. Analysts associate target price direction as being indicative of what the stock recommendation direction should be, which means that target price is considered to be representative of the type of stock recommendation analysts will issue. The null hypothesis 6 is therefore established as follows:

H6$_0$: *Target price is not significantly important in predicting whether analysts will issue stock recommendations that lack market impact*

A variable called target price change (TGTPRCE_CHNG) is constructed to measure the effect of target prices on the determination of buy and sell recommendations. As in Asquith et al., (2005), this variable is the percentage change in the analyst's projected target price for firm j computed as the new target price divided by the old target price

minus 1. Current and previous target prices are obtained from the respective analyst research reports. In cases where the previous target prices are not available in the current reports, such data is obtained from the *First Call* database. It is anticipated that the coefficient on (TGTPRCE_CHNG) will be positive for buy recommendations and negative for sell recommendations.

It needs be mentioned that although target price is considered a representativeness bias in this study, it is actually difficult to know what its role is. It either derives from the stock recommendation, or the stock recommendation follows the target price intuitively set by the analyst, or they are jointly determined. For that reason, although I argue that target price proxies for analyst representativeness bias, it is actually not clear whether target price measures representativeness bias or whether it is a control variable.

3.2.6 Does the existing relationship between the investment bank and the company being researched influence the type of recommendation that analysts issue on a stock?

Analyst compensation or corporate finance relationships between investment banks and their firm clients have been a cause for concern in the recent past. This is because analysts were found to make "buy" and "strong buy" recommendations for stocks which were not necessarily undervalued, but because their investment bank employers could earn significant fees on corporate finance transactions. Analysts would also be rewarded for their part in promoting these deals via additional compensation (Financial Times, April 10, 2002). The null hypothesis 7 is therefore formulated as follows:

H7$_0$: An analyst issues buy recommendation on the stock if there is an existing relationship between investment banks and their firm clients, and a sell if such a relationship does not exist.

A variable called INVEST_RELATE is constructed to measure the relationship between the company being researched and the investment firm which employs the analyst. This variable takes the value of 0 if no relationship exists between the firm and the brokerage

house, 1 if the brokerage house is an underwriter[2] of the firm or has current holdings[3] in the firm, and 2 if the brokerage firm is both an underwriter and has a current holding. Information about the relationships between companies and brokerage houses is found in the disclosure section of analysts' research reports. The coefficient of INVEST_RELATE is expected to be positive for buys and negative for sells. That is, firms which have some form of relationship with the investment bank are more likely to receive buy recommendations while firms with no such relationship are more likely to receive sell recommendations, *ceteris paribus*.

3.3   Control variable

A control variable is used to ensure that the test of the relation between recommendation type and regressors are not confounded by analyst following.

3.3.1   Analyst following

Analyst following is perceived to be essential for the valuation of the firm. Bhushan (1989) and Hussain (2000) observe that the number of analysts following a stock is positively related to the number of institutions holding the firm's shares, the percentage of the firm held by institutions, firm return variability, and firm size. For example, large firms are found to have a larger analyst following than small firms. O'Brien and Bhushan (1990) and Hussain (2000) note that analyst following is higher for industries with regulated disclosures and with a higher number of firms. Lang and Lundhom (1996) document a positive association between analyst following and analyst forecast accuracy.

Alford and Berger (1999) model analyst following, forecast accuracy and trading volume as simultaneous determinants of firms' information environments. They find that analyst following is positively associated with accuracy and trading volume and higher for regulated industries. Characteristics of the analysts' job play a role in

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[2] 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.
[3] Current holding means one of the management team owns shares in the company being researched or does some work for the company.

inducing coverage. For instance, analysts face start-up costs (McNichols and O'Brien, 1997) such as learning about the firm's products (Mikhail et al., 1997).

The variable ANALY_FOLL is the total number of analysts following the firm from *IBES*. It is postulated that there is some indirect relationship between the number of analysts following the firm and the recommendation issued i.e., the larger the firm (in terms of size) the greater the analyst following. Large firms are postulated to have an influence on the type of recommendation issued. Therefore the coefficient of ANA_FOLL is expected to be positive for buy recommendations and negative for sell recommendations.

3.4   Summary

In this chapter I develop testable hypotheses in an attempt to fill the gaps and to answer the research questions that I have identified in the literature in chapter 2. I also discuss how relevant variables will be measured. I first derive the hypotheses that test whether overconfidence and representativeness biases ($H1_0$ and $H2_0$), as measured by the tone of language that analysts use in their research reports, have a significant impact on the type of recommendation that analyst issues. I also derive hypotheses that test whether stock characteristics (i.e., previous price momentum, firm size and book-to-market) influence analysts to issue either new buy or new sell recommendations. Then, I develop hypotheses to test the role of other information issued with stock recommendation (i.e., target price) in influencing analyst's stock rating decisions. Subsequently, I derive hypothesis about the type of recommendation that analyst issues when there is/is not a relationship between the investment bank he/she is working for and the firm being researched. Finally, I provide a variable (ANALY_FOLL) that needs to be controlled for in order to ensure that the tests of the relation between the type of recommendation and other predictors are not confounded.

All hypotheses about research reports characteristics, stock characteristics and target prices are viewed as measures of representativeness bias. It is assumed that financial analysts take the corporate change, the stock's previous price momentum, the size of the

firm, book-to-market and the stock's target price as representative of what type of recommendation they have to issue on stocks they follow.

The next chapter provides a detailed description of the methodology employed to test the hypothesis developed in current chapter.

Chapter 4 Methodological approach

4.1   Introduction

This chapter discusses the research approach and methodologies employed in different stages of my thesis to test the hypotheses laid in the previous chapter. First, I describe the methodology employed to evaluate stock recommendations and target price performance in order to ascertain whether stocks performed according to expectations. Second, I detail the methodology used to select new buy and new sell recommendations that are associated with subsequent stock performance in an opposite direction to the one expected. Third, I describe a content analysis methodology used to measure report-based overconfidence and representativeness bias in order to test hypotheses $H1_0$ and $H2_0$ and finally, I describe the data analysis method used.

The chapter is organised as follows: section 4.2 describes the methodology used to evaluate performance of stock recommendations and target prices. Section 4.3 discusses the method used to select nonconforming stock recommendations. Section 4.4 describes the content analysis method used to test null hypotheses 1 and 2. Section 4.5 discusses the data analysis method used, and section 4.6 concludes the chapter.

4.2   Method used to evaluate stock recommendations and target price performance

The crux of this research is to establish the factors associated with analysts' stock recommendations that lack market impact. For instance, why do some buy recommendations underperform the respective benchmarks, or why do some sell recommendations outperform the respective benchmark after the recommendations are changed from previous categories to the new buy (sell) category? In order to determine whether stocks lack market impact, I first need to evaluate their performance against some appropriate benchmark. In this case, stocks' performance is evaluated against a reference portfolio benchmark over a period of 12 months following the stock recommendation change.

The purpose of this section is to discuss the methodology used evaluate analysts' recommendations and target prices' performance after the stock recommendation is

changed from the previous category to a new buy (sell) category, and after target prices are increased (decreased). In "theory", stocks that receive a buy rating should outperform the relevant benchmark, while new sell rated stocks would be expected to underperform. Similarly, stocks whose target prices increase should outperform the appropriate benchmark, while the ones whose target prices decrease are expected to underperform. Once stock performance is evaluated, the stocks that perform contrary to the expectation 12 months after the recommendations are changed from their previous categories are selected and then analysed further to determine whether there are some factors underlying and influencing them to perform inconsistently with analyst expectations.

Brav and Lehavy (2003) and Asquith et al., (2005) document a significant market reaction to a change in target prices, both unconditionally and conditional on contemporaneously issued stock recommendations. However, the role of target prices that are issued concurrently with stock recommendations is not clear. Target prices are studied together with stock recommendations in this research in order to establish the role of target prices in relation to stock recommendations.

The sample period of this study spans the bull and the bear markets as well as the implementation of Rule NASD 2711. With this in mind, I also assess the performance of both stock recommendations and target prices during the bull and the bear markets, and before and after the implementation of Rule NASD 2711.

There are two main reasons for observing analysts' stock recommendations and target price performance over a period of 12 months after changes in stock recommendations and target prices. One, analysts predict future stock performance over a period of at least 12 months when they make or change their recommendations. For example, all of the top brokerage firms define a buy recommendation as an expectation that the stocks' total return will exceed the industry average (or stocks covered by the analyst) by a certain percentage over a minimum of 12 months depending on the perceived risk (see Appendix 1). Two, the 12 months event period after the recommendation is intended to mitigate the delay in recommendation assimilation documented by Stickel (1995),

Womack (1996), and Ryan and Taffler (2005). Three, Cliff (2004) shows that recommendations have long lives, so it is proper to concentrate on annual results. Other studies such as Michaely and Womack (1999) observe performance of stock recommendations over a period of one year as well.

4.2.1 *Event study methodology*

Event study methodology is used in this study to examine the reaction of investors to changes in financial analysts' stock recommendations and target prices. The methodology is based on the assumption that capital markets are sufficiently efficient to evaluate the impact of new information (events) on expected future profits of firms. Normally, event studies are divided into short-horizon and long-horizon. A short-horizon event study examines stock performance within a short window surrounding the corporate event e.g., one day or a month. Long-horizon studies, on the other hand, measure the effect of the event over the long-term e.g., three years. The relevant event date in this study is defined as the date when the stock recommendation is changed from its current category to new buy or sell categories.

There are pros and cons depending on which of the above time periods is a better measure of performance. An advantage of short-horizon studies is that because daily expected returns are close to zero, the expected return benchmark model does not have a large effect on inferences made about abnormal returns. Use of a short-horizon return window also assumes that any lag in the response of prices to an event is short- lived. However, some studies argue that stock prices adjust slowly to information, so it may be worth examining returns over longer horizons to obtain a full picture of the announcement effect (Fama, 1998). A disadvantage of a long horizon is that abnormal returns are very sensitive to the choice of benchmark (Kothari and Warner, 1997; Barber and Lyon, 1997). However, they also indicate that problems associated with long horizons occur over 3-5 year horizons. The problems associated with long- horizons are unlikely to pose a problem in this study as I restrict the analysis to a one year horizon.

4.2.2 Return generating methodology

The reference portfolio method with the event firm matched on the basis of industry, size and book-to-market (BE/ME) is used as my benchmark approach. Intuitively, matching primarily by industry is appropriate compared with an economy-wide benchmark because analysts often study firms in the context of their industry and specialise in particular industries. Most analysts even prepare a full industry analysis before they conduct specific company 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 (2004) find that analysts take strong cues from recent industry returns in revising the ratings of the stocks they follow. Appendix 1 shows how the top ten brokerage firms in this study define their recommendation categories. Most of them relate expected future stock performance to the respective forecast industry average performance. Industry comparison is used extensively in accounting as a method of analysing firms' financial statements (Palepu, Healy and Bernard, 2000). It is also widely used by finance academics (Womack, 1996; Boni and Womack, 2004).

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

4.2.3 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 (only firms that have data in the CRSP stock return file) into industry deciles

in the manner of Fama and French in their 12 industry portfolios classification process.[4] However, in my case, I use 10 industry portfolios because finance and utilities industries are excluded. Within each industry decile, firms are ranked into thirds based on size, and are then broken down further into groups of three based on their book-to-market ratio. A total of 90 reference portfolios grouped by industry, size and book-to-market are formed. Thus, the stocks in portfolio 1 are stocks in industry 1 and are in the largest size group and within the highest third of the book-to-market ratios.[5] Portfolios are formed in June of each year, starting in June 1991, and monthly returns are calculated for the portfolios for the next 12 months after the portfolio formation date. For each benchmark portfolio, its equally-weighted portfolio return is calculated as an arithmetic return of all securities in a particular industry, size and book-to-market portfolio 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 the *COMPUSTAT* book value of stockholders' equity (*COMPUSTAT* item 60). A six-month lag is considered for book-to-market in order to allow for delay in the publication of annual financial statements (Barber and Lyon, 1997). Thus, the book-to-market ratio for December 31, 2000 is the book value from July 1, 2001 to June 30, 2002 divided by the market value on December 31, 2000.

4.2.4 Calculating abnormal returns

For each sample firm, its abnormal return is computed by deducting the portfolio return from the actual firm return as follows:

$$AR_{it} = R_{it} - E(R_{pt}) \qquad\qquad (4\text{-}1)$$

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[4] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. Excluding financials and utilities in Fama–French 12-industry portfolios classification leaves 10 industries. These 10 industries are used in the first level of classification.

[5] For a robustness, I also reversed the criteria and sorted by industry, book-to-market and size. All my results remained the same.

Where AR_{it} is the abnormal return on security *i* for period *t*, R_{it} is the realised return on security *i* for period *t* and E (R_{pt}) is the expected return for the particular reference portfolio benchmark for period *t*. Because analysts make stock recommendations and predict target prices over the next 12 months (see Appendix 1), the buy-and-hold abnormal return (BHAR) is calculated as the difference between a firm's buy-and-hold return (R_{it}) and the buy-and-hold return on the reference portfolio E (R_{pt}) over the period commencing with the beginning of the month following the recommendation or target price change and ending 12 months later. The BHAR is given as follows:

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

(4-2)

Some stocks are delisted between the time the change in stock recommendation and target price occurs and before the end of the 12 month period. For all stocks that have missing returns after their stock recommendations or target prices are changed, the return on the corresponding reference portfolio is deemed to be its realised return. Thus, for all these stocks the abnormal return subsequent to delisting is zero. The assumption is that once the stock is delisted, investors will roll their remaining investment in the delisted firm into the reference portfolio (Barber and Lyon, 1997).

The buy-and-hold-abnormal return (BHAR) metric is used in preference to cumulative abnormal returns (CARs) in this study because it accurately represents investors' long term experience (Barber and Lyon, 1997). The benefit of using BHARs is further demonstrated by Ikenberry et al., (1995) who show that CARs should be regarded as descriptive in nature because they do not represent a realistic strategy, while BHARs represent a more feasible strategy. The problems associated with BHARs mentioned by Fama (1998) are more pronounced in long-term studies (i.e., more than one year) and are, therefore, unlikely to pose a problem in this study.

4.2.5   *Multiple stock recommendations and target prices*

Both stock recommendations and target prices are characterised by multiple observations for the same firm. Multiple observations arise when a change in stock recommendation or target price by one analyst is followed by other analysts who change their views on that stock as well. This behaviour of analysts is often described as herding.   In most cases herding analysts will make the same change in their recommendations or target prices as did the first analyst. For example, analyst A changes a recommendation on stock X to a buy in May, and before the end of May, analyst B changes the recommendation on the same stock to a buy, and so do analysts C and D in June and July respectively. This means that stock X may have had several recommendations of the same type within a period of few months from the first new buy recommendation. It is believed that too many recommendations on the same stock within a short time period may create a confounding effect when determining stock performance. The resulting cross-sectional dependence from the multiple observations may also lead to overestimation of the significance of the results (Mikhail et al., 2004).

Different studies deal with the issue of multiple recommendations differently. For example, Stickel (1995) drops from the analysis all changed stock recommendations which change again within six months. Ho and Harris (1998) exclude all clusters of reports on a company when multiple reports on a company occurred within a three-week period. Mikhail et al., (2004) use three different approaches in dealing with this problem. These methods are: one, they use only observations for firms that have no other recommendation revisions occurring during the return accumulation period. Two, they combine individual revisions for the same firm in estimating the variance-covariance matrix and compute the t-statistics using the Huber-White estimator. Three, they use Fama and Macbeth (1973) methodology with Newey and West standard errors. With this method, dependence arising from multiple observations for the same firm is eliminated during the same month. In the same spirit, to mitigate this cross-sectional dependence arising from multiple observations, and consistent with Stickel (1995), all recommendations and target prices of the same type that are changed within a period of six months of the first change (either made by the same broker who made the first change or a different broker) are dropped from the analysis.

4.3 Method for selecting nonconforming stocks

In the preceding section, I have discussed the method used to evaluate performance of stocks over a 12 month period. In this section, I discuss the method used to select stocks that have not performed as expected by the analyst, i.e., new buy (sell) recommendations that underperform (outperform) the reference portfolio benchmark over the 12 month period after stock recommendations are changed.

In theory, a 'buy' recommendation is issued when a stock is perceived to be undervalued. Conversely, a 'sell' recommendation is issued when a stock is believed to be overvalued, while a stock awarded 'hold' is believed to be fairly priced. The definitions of stock recommendations by the top ten brokerage firms follow this same idea but go even further in specifying the actual percentages by which the stocks that are classified to each of the three categories are expected to outperform/underperform the respective industry averages. Generally, according to brokerage firms, a buy (sell) recommendation is expected to outperform (underperform) the industry benchmark by at least 10% or higher, depending on risk. Appendix 1 provides detailed information on how different brokerage firms define the recommendations' ratings.

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

The cut-off of 10% is subsequently increased to 20%. Thus, only new buy (sell) recommendations that have underperformed (outperformed) by 20% are considered nonconforming. The reasons for increasing the cut-off point to 20% are as follows:

a) The gist of this study is to investigate the factors influencing analysts' decisions to issue stock recommendations that lack market impact. Increasing the cut-off point to 20% means looking at extreme cases. I believe that analysing extreme cases provides us with a clean test of what factors influence analysts' decisions on stock recommendations.

b) The sample for nonconforming stocks is much larger than I expected, this is the case particularly for new buy recommendations. Increasing the cut-off point to 20% reduces the sample to a reasonable size as I have to manually collect data for other variables such as compensation and target prices for my main analysis.

4.4 Content analysis method used to garner data for overconfidence and representativeness biases in analysts' research reports

The data for null hypotheses 1 and 2 in chapter 3 is collected using computerised content analysis. The content analysis software used is called *Diction*. *Diction* is a package that examines a text for its verbal tone across five variables namely: optimism, certainty, activity, realism and commonality. *Diction* analysis has a theoretical basis in what is referred to as a systematic approach to language study. The focus of the systematic approach is how linguistic structures are exploited in narrative construction. This focus on strategic narrative construction, what might be termed persuasive and rhetorical narralogy, renders the use of *Diction* particularly attractive (Sydserff and Weetman, 2002). *Diction* is particularly appealing in this research because the language that analysts use to justify their stock rating is thought to be at best rhetorical.

The use of *Diction* is well established in the applied linguistics literature (e.g., Hart, 2001). Its validity and reliability as a computerised content program has been widely attested to (e.g., Morris 1994). *Diction* has been mostly used in accounting applications but less so in finance. Ober et al., (1999) limit their study to *Diction's* "certainty" variable only and find no significant difference in the use of certainty in the narratives of "poor performers" when compared to "good performers". Sydserff and Weetman (2002) use *Diction* across its five main variables in their study of impression management in accounting narratives. Although the results from tests of differentiation

between "good performers" and "poor performers" are mixed, they argue that managers of "poor performers" will use impression management to make their narratives resemble as closely as possible the verbal tone of "good performers". The paper advocates that the use of *Diction* merits further exploration in accounting studies. Fogarty and Rogers (2005) use *Diction* in conjunction with other content analysis software to study financial analysts' reports and conclude that analysts' reports are characterised by bias, skew and lack of science. This study builds on Fogarty and Rogers (2005) by applying *Diction* to analysts' reports, but with the specific intention of measuring analysts' psychological biases.

Diction software is chosen because: (a) it uses a series of dictionaries to search a passage for semantic features and allows the researcher to create additional custom dictionaries for particular research needs; (b) it is objective in that the researcher cannot impose his/her own meaning to the text, and (c) it processes information swiftly and therefore facilitates the researcher in deriving the meaning in a particular text. Sydserff and Weetman (2002) further show that it is simple to use, it is automated, yet it possesses a considerable degree of sophistication. The *Diction* dictionaries have been constructed by experts in linguistics. In addition, with a total word corpus of 10,000, *Diction* is considerably more comprehensive than existing form-oriented word-based approaches to content analysis. Its automated nature, both for coding and quantification renders it attractive as a research instrument (Sydserff and Weetman, 2002).

Diction makes a modest, statistical accommodation for homographs, words spelled the same but having different meanings (for example, "lead" – a quality of command or a metal found in nature). Benign homographs are ignored, but confounding homographs are weighted differentially (Hart, 2001). This statistical accommodation for homographs strengthens the content validity of the analysis (Ober et al., 1999). To help the user keep in mind the possible danger of quantifying language behaviour, *Diction* reproduces the text being analysed, alongside its statistical results for convenient checking (Hart, 2001). Thus the user is able to analyse language quantitatively and qualitatively, thereby increasing the reliability and validity of the findings (Ober et al., 1999).

4.4.1 *Actual analysis of reports*

In order to carry out the textual analyses using *Diction*, analysts' research reports are stripped of their header information, tables and graphs, leaving only the actual written narrative used to justify the stock rating. Each of the recommendation justifications is then saved into a text only document and converted into a *Diction* input file to allow the software to construct a single verbal narrative for it. Using a series of words drawn from its internal dictionaries, *Diction* classifies the use of particular words into five master variables which the program assumes best capture the major tonal features of the text: certainty, optimism, activity, realism and commonality.

Only three *Diction* variables are used in this study, and these are: optimism, certainty and activity, because they serve as good proxies for my two key cognitive biases of interest well documented in the behavioural finance literature: namely overconfidence and representativeness (see section 1.5). *Diction* variables optimism and certainty are used to serve as proxies for overconfidence. Optimism is defined in *Diction* as language endorsing some person, group, concept or event, or highlighting their positive entailments. Certainty is defined in *Diction* as language indicating resoluteness, inflexibility, and completeness and a tendency to speak *ex cathedra*.

Diction variable activity is used to serve as a proxy for representativeness. In *Diction*, activity is defined as language featuring movement, change, and the implementation of ideas and the avoidance of inertia. Generally activity implies that a high degree of activity within a company, such as mergers and acquisitions and change of management, may be seen as having a positive impact on the future performance of the stock and may be used by analysts to justify the stock rating they make. Representativeness refers to judgements based on stereotypes (Tversky and Kahneman, 1974). I argue that analysts use the events happening within the company as stereotypes that help them decide on the company's stock recommendation. Rogers and Fogarty (2005) show that analysts are possibly predisposed towards managerial plans and corporate change, and tend to be positive about what management plans to do.

4.5 Data analysis method

The null hypotheses state that overconfidence bias (as measured by OPTIMISM and CERTAINTY), representativeness bias (as measured by ACTIVITY, PRICE_MOM, FIRM_SIZE, BTOM and TGTPRCE_CHNG) and corporate relationships (as measured by INVEST_RELATE) do not have any significant impact on the nonconforming stock recommendations that analysts issue. These hypotheses are tested by cross sectional binary logistic regression. This model describes a linear relationship between the logit dependent variable, which is a log of odds, and a set of predictors.

The dependent variable is RATING. RATING equals 1 if analysts issue new buy recommendations which underperform their respective benchmarks by at least -20% and 0 if new sells are issued that outperform their respective benchmarks by at least +20%. The maximum likelihood estimation is used to estimate the model parameters $\{\beta\}$.

4.6 Summary

In this chapter I describe the methodologies employed to test the hypotheses stated in chapter 3. Firstly, I discuss the event study methodology procedures followed to evaluate stock recommendations and target price performance. Secondly, I describe the methodology employed to select stock recommendations that are performing contrary to expectations. Thirdly, I discuss the content analysis methodology used to collect data for measuring overconfidence and representativeness biases as measured by the tone of language used by financial analysts in their research reports and I conclude with a brief discussion of the data analysis method used in this study.

In the next chapter, I discuss the methodology and results obtained from my pilot study. The pilot study is a simplified process aimed only at testing the efficacy of the content analysis methodology used to garner data for textual proxies of overconfidence and representativeness biases.

Chapter 5   Pilot study

5.1   Introduction

My main study is aimed at investigating factors associated with analysts' issue of "nonconforming" new buy (sell) recommendations. I argue that analysts issue stock recommendations which do not perform as expected because in the process of gathering, analysing and interpreting data about stocks they follow, they tend to be influenced by certain factors, and in particular they are influenced by the cognitive biases. Studies such as those of DeBondt and Thaler (1990) document analysts' cognitive biases and show that analysts have a tendency to overreact and form expectations that are too high. Eastwood and Nutt (1999) demonstrate that analysts underreact to negative earnings news but overreact to positive news and therefore appear systematically optimistic. Most studies investigating analysts' cognitive biases concentrate on stock price reaction to analysts' stock recommendations but fail to trace the psychological biases to the way the analysts prepare their research reports, i.e., they do not examine analysts' textual data.

Fogarty and Rogers (2005) suggest that academic research should not concentrate on the direction of the analysts' bottom lines (i.e., stock recommendations and earnings forecasts) but should conduct textual analysis as well. In their study, they examine financial analysts' textual data and conclude that analyst output is characterised by three elements: influence, skew and lack of science. Influence refers to the fact that analysts' decisions are influenced extensively by the information they obtain from management; skew refers to how the existence of corporate plans, merger/acquisition talk or any suggested change in direction by the company influences analysts; and lack of science refers to the fact that analysts believe that past performance predicts future performance. From their argument, it appears I could understand the models of human behaviour by examining their textual data not just numerical data.

In the previous chapter, I described methodologies employed at different stages of my research. The current chapter aims at testing whether the content analysis methodology and *Diction* variables can serve as good proxies for analysts' overconfidence and representativeness biases. Analysts' psychological biases are integral in this research.

The textual data examined in this pilot study is the tone of language that analysts use in the reports that they prepare to justify their recommendations.

I carry out a pilot study only on my content analysis method because it is a relatively new approach in the context in which I am using it. Content analysis, using *Diction* software has been carried out on analysts' research reports before (e.g., Fogarty and Rogers, 2005). However, their study was not in the context of using *Diction* variables to serve as proxies for specific psychological biases. It is therefore, necessary to make sure that my content analysis methodology will work in my main study. On the other hand, other methodologies, such as the event-study methodology, are well established in the finance literature and thus, do not need to be piloted.

The chapter is organised as follows. Section 5.2 presents the objectives of the pilot study. Section 5.3 presents pilot data. Section 5.4 discusses the methodology used in the pilot to test the relationship between new buy (sell) recommendations. Section 5.5 outlines pilot results while section 5.6 discusses and summarises the pilot results.

5.2   *Objective of the pilot study*

My pilot study textual analysis is conducted on the research reports that analysts prepare to justify their stock recommendations. The aims of this pilot study are twofold. First, it assesses whether *Diction* software variables can be used as proxies for analysts' cognitive biases, in particular, overconfidence and representativeness. Second, it determines whether there is any relationship between the five *Diction* master variables and the type of recommendations that analysts issue. The relationship between the type of stock recommendation and *Diction* variables is established through the use of the logistic regression method. The main reason to seek to infer analysts' cognitive biases from their textual data is because it is difficult to measure analysts' thinking and the way they make decisions outside the psychological laboratory. I believe, however, that I can understand relevant aspects of the analysts' psyche from what they write.

5.3   Pilot data

The data for this study is drawn from analysts' stock recommendations made by the ten US brokerage houses which are ranked among the top ten global investment banks in the *Institutional Investor Survey* (*Institutional Investor*, Dec 2001). Analysts' research reports which they prepare to justify the change in the recommendations they issue form my dataset. These reports are downloaded from the *Investext Plus* database which provides reports and forecasts prepared by top Wall Street and international brokerage firms. Only stock recommendations for US-based companies are looked into and only the changes in stock recommendations (not reiterations) are analysed.

Stock recommendation changes are identified by a detailed search of the terms "upgrades and downgrades" in *Investext Plus*. However, only changes made between September, 1999 and November, 2002 are considered in the pilot. A total of 109 stock recommendations are downloaded from the database, of which 11 are eliminated from the sample because the change in stock recommendation is from "buy to "strong buy" and vice versa, in which case it is assumed that such stock recommendation changes do not comprise a change in a rating category. One company is eliminated because it is a UK-based company. The remaining total sample consists of 97 stock recommendations changes comprising 47 new buy and 50 new sell recommendations. All these stock recommendation research reports show the date and time that the recommendation was made, the name and ticker symbol of the company, brokerage firm and analyst producing the comment, and the text of the comment.   Where there are multiple recommendations relating to the same firm only one recommendation is randomly selected. Compared to other sources of brokerage information, such as *Institutional Brokers' Estimate System (IBES), Investext plus* relies on coding of the written reports that are released by the brokerage firms, which may produce two specific inclusion errors. First, not all comments made by brokerage analysts become disseminated in written reports; second, the reports are often dated some time after the "morning comments" that they reflect (Womack, 1996). However, this does not pose a problem in my main study because *IBES* data is used.

Only changes in recommendation are looked into, partly because they would be among the most prominent news items in a typical day and the most likely to be conveyed immediately to important institutional investors (Womack, 1996), but mainly because changes in recommendations are found to have more information content than reiterations (e.g., Francis and Soffer, 1997). For purposes of this pilot, effort was made to ensure that the proportion of buy recommendations was almost equal to the sell recommendations. However, in reality new buys far exceed new sells (Womack, 1996; Ho and Harris, 1998; Stickel, 1995 and Ryan and Taffler, 2005). As a result my sample is biased in favour of new sell recommendations.

There are a few notable differences between the data used in the pilot study and the data in my main study:

a) The pilot is a simplified version of the main study in that I do not select buy (sell) recommendations that have underperformed (outperformed) any benchmark, but just the recommendations that changed from previous categories to buy or sell categories. This is because at the time that the pilot study was carried out, I did not have data for my main study, specifically the *IBES* database, from which to obtain a complete set of analysts' stock recommendations and the *CRSP* database for the stock returns data.

b) The period for the pilot does not cover the same period as the main study. Thus, the pilot covers between September, 1999 and November, 2002 while the main study covers the period between January, 1997 and December, 2003.

c) In the pilot, I used all five *Diction* variables, namely Certainty, Optimism, Activity, Realism and Commonality (see Appendix 2 for a comprehensive definition of these variables). However, in the main study, only the first three variables (Certainty, Optimism, Activity) that are found to be significant in predicting the type of recommendation that the analyst is likely to issue in the pilot study are used. A closer look at these variables also reveals that they can also serve as good proxies for analysts' psychological biases. For instance,

certainty and optimism serve as good proxies for overconfidence while activity serves as a good proxy for the representativeness bias.

d) In order to identify stocks that received a change in recommendation in the pilot study I used a word search of the terms "upgrades and downgrades" whereas in the main study I tracked the movement of stock recommendations for all companies in *IBES* for the period between January, 1997 and December, 2003. The method used in the main study, not surprisingly, results in a larger dataset than the one used in the pilot.

5.4 Methodology for testing the relationship between new buy (sell) recommendations and Diction scores

The methodology used to obtain data for *Diction* variable*s* which serve as proxies for analysts' psychological biases is as described in chapter 4, section 4.4.

The binary logistic regression model is used to test the relationship between new buy (sell) recommendations and *Diction* variables. The dependent variable is RATING. RATING is 1 if an analyst issues a new buy recommendation and 0 otherwise. The independent variables are *Diction*'s scores which are Certainty, Optimism, Activity, Realism and Commonality. The maximum likelihood estimation is used to estimate the model parameters. The logistic model is specified as follows:

$$RATING = LOGIT\ (\pi) = LOG \left(\frac{\pi}{1-\pi} \right)$$
$$= \alpha + \beta_1 OPTIMISMj,t + \beta_2 CERTAINTY_{j,t} + \beta_3 ACTIVITY_{j,t}$$
$$+ \beta_4 REALISM_{j,t} + \beta_5 COMMONALITY_{j,t}$$

(5-1)

5.5 Pilot Results

Table 5-1 shows that a test of the full model and with five predictors is statistically reliable, Chi-square = 23.991, p < 0.0005, indicating that the predictors as a set reliably distinguish between buy and sell stock recommendations. Optimism, Certainty and Activity in the tone of language used in analysts' research reports that they draw to

justify their recommendations are individually reliable in predicting analysts' stock recommendations. The parameter estimates for this variables are -0.491, -0.119 and -0.148 respectively. Optimism is significant at 0.1% level, Certainty at 10% level and Activity at 5% level. Overall, the model shows that, for example, the less certain analysts are, the more likely their recommendation will be a "sell", and the more optimistic, the more likely their recommendation will be a "buy". On the other hand, the greater the level of activity/change within the company such as change of management or a firm's eminent merger and acquisition, the more likely their recommendations will be "buy". Realism and Commonality are non-significant.

Table 5-1 Determinants of new buy/sell recommendation using _Diction_ five master variables

This table presents the logit regression on five _Diction_ master variables. The dependent variable is the stock rating. For each variable, the coefficient estimate, Wald chi-square and significance level are presented in columns 3-5 respectively

Variable	Predicted sign for sells	Coefficient estimate	Wald chi-square	Significance level
Certainty	-	-0.119	3.118	0.077*
Optimism	-	-0.491	11.727	0.001****
Activity	-	-0.148	4.972	0.026**
Realism	+	0.072	0.742	0.389
Commonality	-	0.002	0.001	0.980
Constant		33.765	9.934	0.002
Cox and Nell R^2		=	22%	
Nagelkerke R^2		=	29%	
N: Buys		=	47	
Sells		=	50	

****,***, **, and * denote significance at 0.1% 1%, 5% and 10% levels, respectively

In summary, the results from the relationship between stock recommendation and psychological biases as measured by _Diction_ scores can be interpreted as demonstrating that new buy (sell) recommendations are associated with a higher (lower) degree of optimism and certainty together with an increased (decreased) level of activity. On the basis of this pilot, there appears to be a potential relationship between _Diction_ scores (Optimism, Certainty and Activity) and the associated stock recommendations made by analysts. Thus, psychological biases as measured by Optimism, Certainty and Activity are associated with the buy and sell recommendations which financial analysts issue.

5.6   *Discussion and summary of pilot results*

There are various judgemental biases documented in the behavioural finance literature. These documented biases are measured mainly by the way the market responds to analysts' stock recommendations and earnings forecasts. One of the reasons why the cognitive biases are measured in this way may be because it is difficult to measure analysts' psychological biases outside laboratory experiments. To circumvent this problem, I try to measure analyst bias by analysing the tone of language that they use in their research reports. I believe that I can understand analysts' psyche through what they write. This approach is attested to by other studies including Fogarty and Rogers (2005).

For that reason, in this pilot study, I use a content analysis method, using *Diction* variables (Certainty, Optimism and Activity) to proxy for the most important psychological biases, namely overconfidence and representativeness. Optimism and certainty serve as proxies for overconfidence in analysts' stock recommendations while activity serves as a proxy for the representativeness heuristic.

Overconfidence is defined as overestimating what one can do compared to what objective circumstances would warrant. The results may be interpreted as indicating that analysts believe they have superior investment abilities and tend to overestimate the likely performance of the stocks they follow. Various studies such as Odean (1998b) and Barber and Odean (2001) have attested to investors' overconfidence bias.

Representativeness refers to judgements based on stereotypes (Tversky and Kahneman, 1974). The results show that the high level of activity (activity is defined in *Diction* as the language featuring movement, change and the implementation of ideas and the avoidance of inertia) within the company is believed to be good for the stock and vice versa. In other words, activity is seen as representative of future stock performance. Fogarty and Rogers (2005) confirm that financial analysts make positive recommendations about stocks if they are aware of the company's broad range of future plans for change including mergers and acquisitions and they tend not to be critical enough about prospective merger activity.

In summary, the two cognitive biases (overconfidence and representativeness) appear to be associated with analysts' decisions. These biases may lead analysts to be overly optimistic when analysing likely future stock performance. Analysts might then exaggerate the likely returns to be derived from investing in particular stocks and ignore the potential pitfalls.

In this chapter, I have established the critical link in my research in terms of how to proxy analysts' overconfidence and representativeness biases using *Diction* variables. The next chapter describes my main study samples of new stock recommendations and new target prices.

Chapter 6 Data, data sources, sample selection and sample description

6.1 Introduction

The previous two chapters discuss the methodologies used at different stages of my research and a test, in a pilot study, of whether the content analysis method I use to proxy for analysts' psychological biases is efficient. The main purpose of this chapter is to provide a broad description of how I collected my samples of new buy and new sell recommendations and my samples of increased and decreased target price stocks. Although I do not focus on new hold recommendations in my empirical analysis, the data for new hold stock recommendations and their description are included in this chapter in order to provide a complete and clear view on US analyst stock recommendations.

The essence of this study is to investigate the factors associated with financial analysts' stock recommendations that lack market impact. Therefore, I need a sample of new buy and new sell recommendations so that I can evaluate their performance and determine if they do/do not lack market impact. Parallel to the analysis of stock recommendations, I also evaluate the performance of analysts' target prices. Analysing target prices concurrent with stock recommendations is compelling in this study, partly because both are important analysts' outputs and analysts use both together or in isolation when they give advice about the likely future performance of stocks. However, importantly, Brav and Lehavy (2003) argue that in recent years financial analysts have been increasingly disclosing target prices in their equity reports, suggesting that target prices have become more important to investors in their investment decision-making processes, although they do not make clear what the role of stock recommendations that are issued concurrent with stock recommendations is.

The chapter is organised as follows: section 6.2 describes my new stock recommendation and new target price data sources, section 6.3 describes the sample selection process for both new stock recommendations and new target prices, and section 6.4 provides a sample description of both new stock recommendations and new target prices, and section 6.5 concludes the chapter with a discussion and a summary.

6.2   Data source

This section provides information about my stock recommendation and target price samples as well as a general description of their data sources.

6.2.1   Analysts' stock recommendations data source

The source of analysts' stock recommendations used in this research is the Institutional Brokers' Estimate System (*IBES). IBES* keeps two stock recommendation databases namely, a detailed history recommendation database and a summary recommendation history database. The detailed history recommendation file provides a database record for each recommendation change made by different analysts/brokerage firms. Attributes of this file include names of analysts and brokerage houses issuing the report, previous and current recommendation, date of change in recommendation and company name (using ticker number). The summary history recommendation file gives monthly snapshots of each company followed by brokerage firms subscribing to *IBES*. The summary history database provides information regarding the average consensus rating level, the standard deviation of stock ratings and the number of analysts downgrading or upgrading their opinion in a month. My sample of buy and sell recommendations is from the *IBES* detailed recommendation file.

The initial stock recommendation sample I compile covers the period from January 1, 1997 through to December 31, 2003. My final sample consists of stock recommendations issued by the top ten US brokerage firms as identified in the December 2001 issue of the *Institutional Investor* surve*y*. The *Institutional Investor* annually ranks research departments and security analysts of major US brokerage firms mainly according to the polls of institutional investors (Womack, 1996).

Different brokerage firms use different stock rating systems e.g., "buy", "accumulate", "attractive", "outperform", "neutral", "neutral weight", "market perform", "peer perform", "reduce", "underperform", "sell". However, upon receiving these ratings *IBES* recodes the recommendation ratings into five categories "strong buy", "buy", "hold", "underperform" and "sell". The *IBES* classification is further reclassified in this

research into the most simple and commonly used stock rating systems consisting of just "buy", "hold" and "sell" in order to allow for easy and intuitive interpretations of quantitative 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 used.

Only changes in recommendations and not reiterations are included in the sample because changes in recommendations are found to have more information content than reiterations (e.g., Francis and Soffer, 1997). Changes in stock recommendation are defined as the current recommendation minus the previous recommendation. The changes examined are new buy recommendations from sell and hold, and new sell recommendations from buy and hold.

6.2.2 Analysts' target prices

My target price data are provided by *First Call*. *First Call* provides database records of each target price issued by different brokerage firms. Typical information contained in the target price database include companies' symbol (equivalent to ticker number), brokerage firm issuing the target price, current and previous target prices as well as the date on which the target price is issued and changed. As with stock recommendations I include only target price changes (not reiterations). Target prices are regarded as changed if they have either increased or decreased from their previous levels. Unlike stock recommendations, target prices have only two rating levels, i.e., it is either that the analysts' target price is higher than it was previously (increased) or lower than it was previously (decreased).

6.3 Sample selection process

This section looks at the process of selecting samples of analysts' stock recommendations from the population of stock recommendations available in the *IBES* database and target prices from the population of analysts' target prices available in the *First Call* database.

6.3.1 Stock recommendations

Table 6-1 shows that the January 2004 *IBES* database contains a total of 363,158 observations. Observations represent the issuance of stock recommendations by a particular brokerage firm for a specific company between the years 1985 through to December 2003. Eliminating the recommendations not issued by top-ten brokerage firms, reiterations, utilities and financials firms leaves a total of 16,198 changes in recommendations. Each stock with changes in recommendation must have its market price information available in the *Chicago Research in Security Prices (CRSP)* database at least at the time that the change in recommendation is made. About 2,029 changes in recommendations for some US firms or non-US firms (overseas firms listed on NYSE/NASDAQ/AMEX) are eliminated from the sample because there is no stock data on them in the *CRSP* database. The final sample consists of 14,169 changes in recommendations

Table 6-1 Sample selection process – stock recommendations

Procedure	Number of observations
Total recommendations available in *IBES* database by January 2004	363,158
Less recommendations made by other brokers	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 analyst or other Analyst	60,046
	20,164
Excluding utilities and financials[6]	3,966
Total excluding utilities and financials	16,198
Eliminate US and non-US stocks with no data in CRSP	2,029
Total recommendation changes	14,169

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

6.3.2 Target prices

Table 6-2 shows that the April 2004 *First Call* database had a total of 565,466 target prices that were issued by the top ten brokerage firms between January 1, 1997 and December 31, 2003. Eliminating reiterated target prices, stocks of US and non-US (overseas firms listed on NYSE/NASDAQ/AMEX) firms without stock data in the *CRSP* database as well as financials and utilities sector firms results in a final change in target price sample of 57,466 cases.

Table 6-2 Sample selection process – target prices

Procedure	Number of observations
Total target prices available in *First Call* database by April 2004	1,696,312
Less target prices issued by non-top ten brokers	1,129475
Target prices issued by the top-ten brokers	566,837
Less target prices issued before Jan 1, 1997 and after Dec 31, 2003	1,371 [7]
Recommendations issued between Jan 1, 1997 and Dec 31, 2003	565,466
Less reiteration of previous target prices	487,473
	77,993
Less US and non-US stocks with no data in the *CRSP* database	6,776
	71,217
Excluding utilities and financials	13,751
Total target price changes	57,466

6.4   Sample description

This section provides a description of both the initial stock recommendation and target price samples. Although new buys and new sell recommendations are the two main categories of interest in this research, this section also describes a sample of new hold

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[7] The *First Call* database commenced around the beginning of 1997. This may explain why I have too few target price forecasts cases issued outside the sample period in the database.

recommendations so that I can have a full understanding of all categories of analyst stock recommendations.

6.4.1 Description of analysts' stock recommendations

Table 6-3 Panel A provides information about the duration (in calendar days) of the stock recommendation in a previous category before it is changed to a new category by the same broker. This information is important because it provides a rough idea about the frequency of stock recommendation revisions. Not surprisingly, on average, recommendations spend the shortest average period of time (in days) in the sell category before they are upgraded to either hold (mean number of days = 159) or buy (mean number of days = 180) respectively. On the other hand, it takes longest for a buy recommendation to be downgraded to sell category (mean number of days = 402) or hold category (mean number of days = 371).

Panel B of Table 6-3 provides the time in months that stock recommendations are outstanding in their previous categories before they are changed into the new category by the same brokerage firm that issued the previous stock rating. This Panel complements Panel A by giving the exact length of time (in months) and the proportion of recommendations that are outstanding in the previous category before a change is made. Approximately 70% of new buy, new hold and new sell recommendations respectively are moved from their previous categories within a period of 12 months. This information provides one justification for examining the future returns (in chapter 7) over at least a 12 months' holding period centred on the report publication date.

Table 6-4 Panel A presents the yearly distribution of stock recommendations (both in total and by recommendation category), yearly ratio of new buy to new sell, and yearly average rating based on the following: buy (1), hold (2) and sell (3). The aim of this table is to assess the rating distribution and the patterns of new buys and new sells over my sample period. Consistent with Barber et al., (2004) this panel shows that the dramatic change in the distribution of stock recommendations is more conspicuous in 2002 where there are 23% buys, 51% holds and 26% sells. During the first half of 2000

Table 6-3   Calendar days between changes of recommendation from the previous recommendation to the new category and distribution of time (in months) that recommendations spent in the previous category before they are changed to a new category

Panel A provides statistics regarding the number of calendar days that the recommendation is outstanding in the previous category before it is changed to a new recommendation category by the same broker who issued the previous recommendation. The first column shows different recommendation change categories, column 2 shows the mean number of days in each category, columns 3 to 5 report the 1st quartile, median and 3rd quartile for the number of days respectively. Panel B shows the amount of time in months that recommendations spent in the previous category before they are changed to a new category. Column one shows the period spent in a category in months, columns 2-4 show the proportion of new buy, new hold and new sell recommendations in their respective categories respectively.

Panel A: Number of calendar days between changes of recommendation from the previous recommendation to a new category				
Recommendation category	Mean	1st Quartile	Median	3rd Quartile
New buy from hold	273	84	189	378
New buy from sell	180	48	32	317
New hold from buy	371	89	244	535
New hold from sell	159	49	117	234
New sell from buy	402	62	226	580
New sell from hold	315	86	217	438

Panel B: Distribution of time (in months) that recommendations spent in the previous category before they are changed to a new category

Period	New buys N = 2799		New holds N = 3501		New sells N = 1331	
	Monthly % change	Cum %	Monthly % change	Cum %	Monthly % change	Cum %
1 month	9%	9%	13%	13%	14%	14%
2 months	10%	19%	8%	21%	6%	20%
3 months	9%	28%	7%	28%	7%	27%
4 months	8%	36%	6%	34%	6%	33%
5 months	7%	43%	6%	40%	7%	40%
6 months	6%	49%	5%	45%	5%	45%
7 months	5%	54%	5%	50%	4%	49%
8 months	5%	59%	4%	54%	5%	54%
9 months	4%	63%	4%	58%	4%	58%
10 months	4%	67%	4%	62%	5%	63%
11 months	4%	71%	3%	65%	3%	66%
12 months	3%	74%	3%	68%	2%	68%
Over 12 months	26%	100%	32%	100%	32%	100%

Table 6-4 Distribution of recommendation, ratio of buy to sell and average rating per year over the sample period and rating distribution from previous studies.

This table reports the yearly distribution of new stock recommendations. Column 1 shows the sample year, column 2 the total number of changes in recommendations in a particular year, columns 3-5 present the total number and proportion of new buy/hold/sell recommendations respectively, column 6 presents the ratio of buy to sell and column 7 reports the mean rating. Panel B provides the examples of stock recommendation distribution in the previous studies. Columns 1-3 show authors of previous studies, prior studies sample periods and rating distribution respectively.

Panel A: Distribution of recommendations, ratio of buy to sell and mean rating across years									
Year	Total Recommenda-tions		Buys		Holds		Sells		Ratio of buy: sell	Mean rating[8]
	Total	%	Total	%	Total	%	Total	%		
1997	433	100%	159	37%	263	60%	11	3%	14.5:1	1.65
1998	1105	100%	450	41%	613	55%	42	4%	10.7:1	1.63
1999	1440	100%	772	54%	633	44%	35	2%	22.0:1	1.48
2000	672	100%	346	51%	319	47%	7	2%	49.4:1	1.49
2000	898	100%	280	31%	599	67%	19	2%	14.7:1	1.70
2001	2129	100%	809	38%	1240	58%	80	4%	10.1:1	1.66
2002	4274	100%	966	23%	2189	51%	1119	26%	0.8:1	2.03
2003	3218	100%	1106	34%	1517	47%	595	19%	1.8:1	1.84
Overall	14169	100%	4888	34%	7373	52%	1908	19%	2.6:1	1.80

Panel B: An example of stock recommendation descriptive statistics from prior studies				
Prior studies	Sample period	Rating percentage		
		% buys	% holds	% sells
Stickel (1995)	1988 -1991	55%	33%	12%
Womack (1996)	1989 -1991	77%	-	23%
Barber et al., (2001)	1985 – 1996	47%	47.2%	5.7%
Barber et al., (2003)	Jan 1996 - Dec 2001	67%	29%	3%
Chen et al., (2003)	Oct 1993 - Jan 2003	59.63%	37.82%	2.55%
Asquith et al., (2005)	1997 – 1999	70.80%	28.7%	0.5%

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[8] The stock recommendations are classified as follows: 1=Buy, 2=Hold, 3=sell

Figure 6-1 Yearly distribution of buys, holds and sells between January 1997 and December 2003
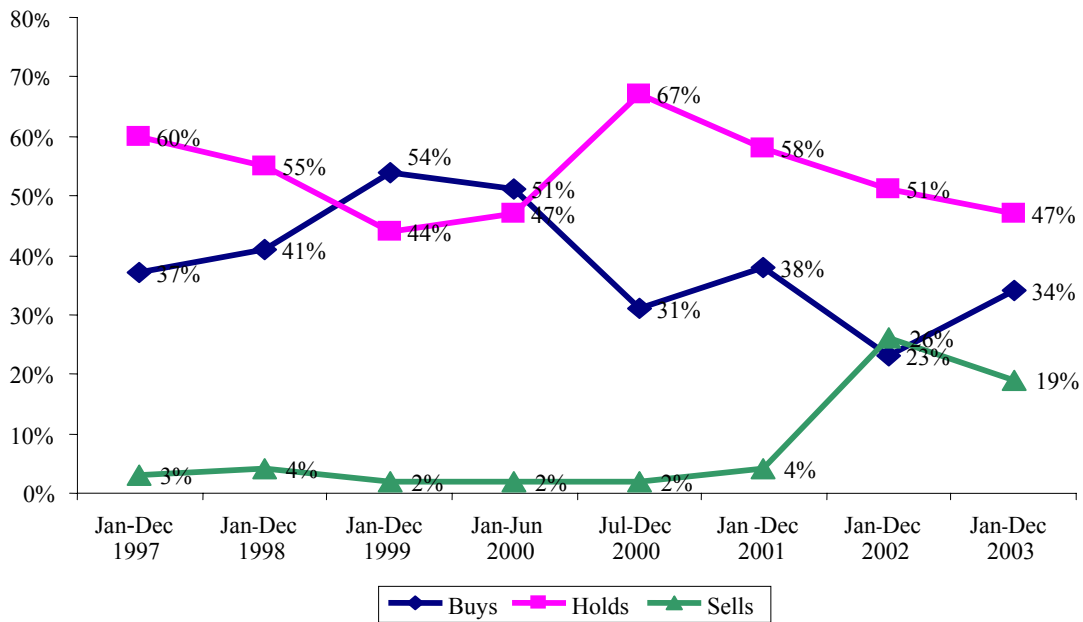
the ratio of buys to sells reached the highest level of 49.4:1 but plunged to 0.8:1 in 2002. Figure 6-1 above provides a clear picture of the distribution of recommendations over time between January 1, 1997 and December 31, 2003. The average rating also reached its all time low (2.03 which is hold) in 2002. While the apparent decline in 2002 may be attributed to other factors such as the economic conditions and the collapse of market prices of that time, it may also be largely due to the implementation of NASD 2711 and Rule 472[9] (Barber et al., 2004; Madureira, 2004) which were effected around the same time (on the July 9, 2002). In general terms, these rules are meant to pressure those brokerage firms who were persistently issuing a relatively high percentage of buy recommendations to adopt a more balanced rating system.

Panel B of Table 6-4 presents the proportion of new buy, new hold and new sell recommendations in the previous studies. The aim of this table is to show the proportion of stock recommendation in some of the previous studies and to make a comparison of their findings with the findings in my sample. Overall, the ratio of buy to sell (2.6:1) observed in this study is more balanced compared to the findings in the previous

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

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studies. Thus, brokerage firms are now issuing more sell recommendations than before. Again, this may be interpreted as an indication that the recent regulations (i.e., NASD 2711 and Rule 472) have been effective. Madureira (2004) points out that this may also be a result of the adoption of new rating systems by eight of the big ten brokerage houses.

The matrix of changes in recommendation for the whole sample period is shown by Table 6-5. About 35% of the 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.

Table 6-5   The transition matrix of changes in recommendations

This table presents the transition matrix of changes in recommendation for my entire sample period, January, 1997 to December, 2003. Old rating is the rating of the stock before it is moved to the new rating category. The transition percentages are shown in brackets.

Old Rating	New rating				
	Buy	Hold	Sell	Total	Total %
Buy	-	6508	278	6786	48%
		(46%)	(2%)	(48%)	
Hold	4739	-	1630	6369	45%
	(34%)		(11%)	(45%)	
Sell	149	865	-	1014	7%
	(1%)	(6%)		(7%)	
Total	4888	7373	1908	14169	-
Total %	(35%)	(52%)	(13%)		100%
	Ratio of buy to sell = 2.6:1				

Over my sample period, analysts are more likely to downgrade stocks than upgrade them (59% versus 41%). About 77% of downgrades are from buy to hold, 19% are

Table 6-6   Total number of firms and financial analysts available in *IBES*

This table presents total number of firms covered and total number of analysts available in *IBES*. Column 1 shows the sample year; column 2 shows the number of firms covered overtime, columns 3-6 show mean, 1st quartile, median, and 3rd quartile of the number of analysts issuing recommendations respectively.

Year	Number of firms covered	No of analysts issuing recommendations [a]			
		Mean	1st Quartile	Median	3rd Quartile
Jan - Dec 1997	296	6.3	3.0	5.0	8.0
Jan - Dec 1998	626	7.0	2.0	6.0	9.0
Jan - Dec 1999	733	8.0	4.0	7.0	11.0
Jan – Jun 2000	449	4.5	2.0	4.0	6.0
Jan - Dec 2000	542	5.0	2.0	4.0	6.0
Jan - Dec 2001	894	7.8	3.0	6.0	10.0
Jan - Dec 2002	1292	9.5	4.0	8.0	13.0
Jan - Dec 2003	1032	9.4	4.0	8.0	13.0
Overall	2068	21.5	12.0	18.0	29.0

[a] These are analysts issuing recommendations on the sample firms each year. This include top ten brokerage firms used in this study

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 recommendation is very rarely from one extreme category to another, i.e., from buy to sell and vice versa. Thus, movement in recommendations is almost always through the hold category.

Table 6-6 reports the total number of firms covered and the average number of all brokerage houses issuing recommendations in *IBES* including the top ten brokerage firms used in this study. The aim of this table is to provide a pattern of analysts' coverage and number of firms covered over time. Both firms covered and average brokerage firms increased over the years but as in Barber et al., (2003) they both dropped in 2001, i.e., number of firms is 894 and mean (median) number of analysts is 8 (6). Overall, there is a median of 18 brokerage firms including the top 10 used in this study following a total of 2,068 firms in the *IBES* database.

6.4.2   Description of analysts' target price and sample firms

Table 6-7 Panel A provides the time in months that the target prices are outstanding before new price forecasts are issued by the same brokerage firms that issued the previous target price. This information gives us an idea of how frequently analysts change their target prices compared with the frequency with which they change their stock recommendations. The results show that, as with stock recommendations, a large percentage of target prices (91% of increased target prices and 87% of decreased target prices) are changed within 12 months.

As expected, Panel B shows that the average number of days that the target prices remain unchanged before being increased is shorter (mean number of calendar days = 127, approximately 4 months) than the number of days that the target prices are reduced (mean number of calendar days = 168, slightly over 5 months).

Table 6-8 shows the yearly distribution of target prices in total/percentage and by category (increase/decrease) and the ratio of increase to decrease in target prices. The total number of target prices declined over time and reached the lowest level in 2000 (target price total = 5029), however, in the subsequent years, the total number of target prices increased and more than doubled by the end of 2003. Figure 6-2 provides a clearer picture of the distribution of increased and decreased target prices over time.

Overall, there are more target prices in the increase (56%) category than in the decrease (44%) category. The percentage of target prices that are increased reached its highest level in the first half of 2000 and thereafter showed a steady decline until reaching an all time low in 2002 where the ratio of increase to decrease falls to 0.53:1. The table shows that 31% of target prices are in the decrease category in the first half of 2000 but rise to 65% in 2002. The total number of firms covered is highest in 2000 making a total of 1,813 but drops in 2001 before recovering in 2002 and 2003. However, I did not ascertain how many of the existing firms are new for each year and overall.

Table 6-7 Distribution of time (in months) target prices spent in the previous category before they are changed to a new category and calendar days between changes of target prices from the previous category to the new category

Panel A shows the mean, 1st quartile, median and 3rd quartile number of calendar days that the target price is outstanding before it is changed to a new target price value by the same broker who issued the previous target price value. The first column shows target price level, column 2 shows the mean number of days in each target price level, columns 3-5 report the 1st quartile, median and 3rd quartile number of days respectively. Panel B shows the amount of time in months that target prices spent in the previous category before they are changed to a new category. Column 1 shows the period spent in months, columns 2-4 show the proportion and cumulative proportions of increased and decreased target prices in each month.

Panel A: The overall number of calendar days that target prices are in their previous category before they are changes to a new value				
Target price	Mean	1st Quartile	Median	3rd Quartile
Increase	127	14	55	124
Decrease	168	21	73	182

Panel B: Distribution of time (in months) that target prices spent in the previous category before they are changed to a new category				
Period	Increased target prices N = 26,297		Decreased target prices N = 21,104	
	Monthly % change	Cum %	Monthly % change	Cum %
1 month	38%	38%	32%	32%
2 months	13%	51%	13%	45%
3 months	13%	64%	12%	57%
4 months	10%	74%	9%	66%
5 months	4%	78%	5%	71%
6 months	3%	81%	4%	75%
7 months	3%	84%	4%	79%
8 months	2%	86%	2%	81%
9 months	1%	87%	2%	83%
10 months	2%	89%	2%	85%
11 months	0.8%	89.8%	1%	86%
12 months	0.8%	90.6%	1%	87%
Over 12 months	9%	100%	13%	100%

Table 6-8 Distribution of target prices, ratio of increase to decrease, average number of firms covered and total number of analysts issuing target prices for the sample firms.

This table reports the yearly and overall distribution of target prices. Column 1 shows the sample year, column 2 shows the total number of target prices for each year and columns 3-4 show the total number and percentage of increase and decrease in target prices over the years respectively. Column 5 shows the ratio of increase to decrease while column 6 shows the number of firms covered each year.

Year	Target price total	Increase	Decrease	Ratio of increase: decrease	No. of firms covered
Jan – Dec 1997	12,334 (100%)	8,477 (69%)	3,857 (31%)	2.2:1	1,708
Jan – Dec 1998	7,338 (100%)	3,875 (53%)	3,464 (47%)	1.1:1	1,401
Jan – Dec 1999	5,845 (100%)	3,716 (64%)	2,129 (36%)	1.7:1	1,350
Jan – June 2000	2,727 (100%)	1,873 (69%)	854 (31%)	2.1:1	925
Jul – Dec 2000	2,302 (100%)	1,266 (55%)	1,036 (45%)	1.2:1	888
Jan – Dec 2001	5,373 (100%)	2,602 (48%)	2,771 (52%)	0.9:1	1,276
Jan – Dec 2002	10,248 (100%)	3,582 (35%)	6,666 (65%)	0.5:1	1,559
Jan – Dec 2003	11,298 (100%)	6,684 (59%)	4,614 (41%)	1.4:1	1,579
Overall	57,466 (100%)	32,075 (56%)	25,391 (44%)	1.2:1	2943

Figure 6-2 Yearly distribution of increased and decreased target prices between January 1997 and December 2003

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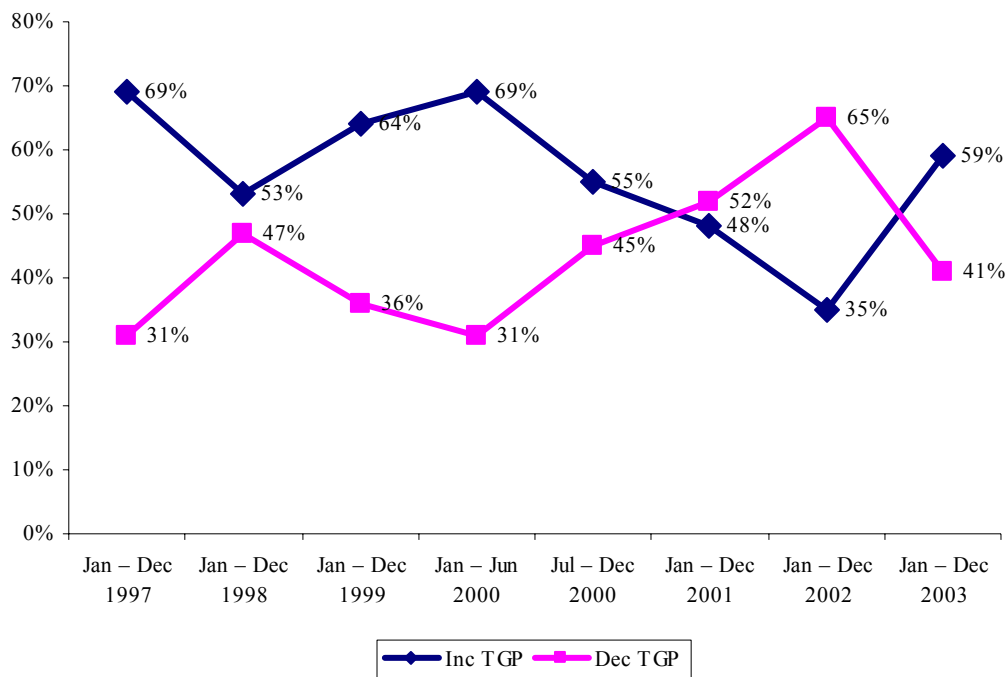
Table 6-9 Distribution of brokerage firms over the sample period

This table reports the distribution of brokerage firms that issued target prices in the *First Call* over the sample period. Column 1 shows the sample years and columns 2-5 shows mean, 1st quartile, median and 3rd quartile respectively for the number of brokerage firms issuing target prices over the sample period.

Year	Number of brokerage firms issuing target prices			
	mean	1st Quartile	Median	3rd Quartile
Jan – Dec 1997	3.8	1.0	3.0	5.0
Jan – Dec 1998	4.3	1.0	3.0	6.0
Jan – Dec 1999	5.0	1.0	3.0	6.0
Jan – Jun 2000	4.4	1.0	3.0	6.0
Jul – Dec 2000	4.3	1.0	3.5	6.0
Jan – Dec 2001	5.4	2.0	4.0	7.0
Jan – Dec 2002	4.2	1.0	2.0	5.0
Jan – Dec 2003	6.2	1.0	2.0	4.0
Overall	7.4	2.0	4.0	10.0

Table 6.9 shows the distribution of brokerage firms over my sample period. Overall, the mean (median) number of brokerage firms available in *First Call* (including the top 10) and issuing target prices on the sample firms is 7.4 (4.0) with the 1st and 3rd quartile values of 4.0 and 10.0 respectively.

6.5   Discussion and summary

Financial analysts' stock recommendations and target prices are important outputs from their work. Financial analysts use both outputs concurrently or separately when they give investment advice to investors. In most cases financial analysts use target prices to justify the stock recommendations they make (Bradshaw, 2002). In this chapter both outputs are described separately. The fact that there is a strong linkage between the two makes it worthwhile to study them together. Univariate analysis of stock recommendations and target prices over the same sample period, i.e., January 1, 1997 to December 31, 2003 provides both striking similarities and differences between the two.

The common qualities between financial analysts' stock recommendations and target prices include: first, a large sample of both is changed from the previous stock recommendation category and target price level respectively to the current category or

level within a period of 12 months. This confirms that financial analysts make predictions about stock performance and stock price over a period of 12 months.

Second, both have a 'preferred' rating level and 'less preferred' rating level. A 'preferred' rating level is a buy for stock recommendations and increased target price for target prices. Interestingly, for both stock recommendations and target prices, stocks reside in the 'less preferred' categories for the shortest period of time compared to the time spent in the 'preferred' categories. This can be interpreted to indicate that financial analysts are reluctant to keep stocks in the poor rating category for long because of the costs to them associated with a poor rating of firms.

Third, not surprisingly, the overall percentage of stocks in the 'preferred' categories outweigh those in the 'less preferred' categories, i.e., 34% is in the buy category compared to 19% in the sell category, and 56% target prices are increases compared to 44% decreases.

Last, both stock recommendations and target prices behave in a similar fashion, suggesting that factors which affect one have an impact on another as well. For example, throughout the sample period, increases in target prices outrun decreases but in the second half of 2000 the number of decreases escalates until they outweigh the number of increases in 2002. A similar pattern is observed with changes in stock recommendations. The ratio of new buys to new sells declined in the second half of 2000 and reached a ratio of buy to sell of 0.8:1 in 2002 from 49.4:1 in the first half of 2000. The evident relationship in the samples of stock recommendations and target prices makes it worthwhile to study both together.

The noteworthy differences between my samples of stock recommendations and target prices are, first, despite the same sample period and the same sample selection process for both, the final sample for target prices is far larger than the sample of stock recommendations. One reason for this may be that target prices are changed much more frequently than stock recommendations, as a result more changes in target prices are observed. For example, 38% and 32% of increases and decreases in target prices

respectively are changed from their previous categories within one month while only 9%, 13% and 14% of new buy, new hold and new sell stock recommendations respectively are changed within a month.

Second, the total number of changes in recommendations increased throughout the years and more than doubled between 2001 and 2002 before dropping by approximately 75% in 2003. In comparison, the total number of target prices decreased over time in the first half of the sample period, reached the lowest level in 2000 and increased again in the subsequent years.

Third, there are some reversals observed in both target prices and stock recommendations patterns at some point in the sample period. For example, throughout the sample years, the increases in target price outweigh decreases but in 2000 there is a reversal that reached a peak in 2002 where decreases in target prices are 65% and increases 35%. With regard to stock recommendations, the reversal happens in the second half of 2000 and reaches a peak in 2002 when new buy recommendations declined to the low of 23% and new sell recommendations increased to an all-time high of 26%. These changes in patterns may be influenced by different factors such as economic conditions but very likely these results from the implementation of new rules and regulations (e.g., NASD 2711) relating to analysts' work. However, we need to note that movement of both stock recommendations and target prices is in the same direction although from different base levels.

In summary, this chapter describes my data, data selection process and samples of both stock recommendations and target prices, and concludes by highlighting the similarities and differences that I observe in the two samples of stock recommendations and price forecasts. It is worth noting that the substantial number of stock recommendations and target prices in my sample from *IBES* and *First Call* respectively demonstrates that both are important financial analysts' outputs which investors use in their investment decision-making processes.

The next chapter provides the results of stock recommendation and target price performance 12 months after a change is effected. The aim of the performance evaluation process is to identify the sub-samples of stock recommendations that have not performed as expected for further analysis in chapter 8.

Chapter 7 Stock recommendation and target price performance and selection of nonconforming stocks

7.1 Introduction

In the previous chapter I have described my sample of new stock recommendations and new target prices. In this chapter, I determine the performance of stock recommendations and target prices 12 months after analysts change them from their previous categories to new buy (sell) and increased (decreased) target price categories. The idea behind this performance evaluation process is to select stocks which perform contrary to expectation 12 months after the recommendations are changed. Subsequently, these stocks (underperforming new buys and outperforming new sells) are analysed further to determine whether there are any underlying factors influencing them to perform inconsistently. In "theory", stocks that receive a buy rating should outperform the relevant benchmark, while new sell rated stocks would be expected to underperform. Similarly, stocks whose target prices increase should outperform the appropriate benchmark, while the ones whose target prices decrease are expected to underperform.

Brav and Lehavy (2003) and Asquith et al., (2005) document a significant market reaction to a change in target prices, both unconditionally and conditional on contemporaneously issued stock recommendations. However, the role of target prices that are issued concurrent with stock recommendations is not clear. To explore this issue, target prices are studied together with stock recommendations in this research. Specifically, target prices are included in the logistic regression analysis in chapter 8 to test the null hypothesis that target prices do not influence the type of rating financial analysts award to the stocks they follow ($H5_0$).

As mentioned in section 4.2.5, to mitigate the cross-sectional dependence arising from multiple observations, all recommendations and target prices of the same type that are changed within a period of six months of the first change are dropped from the analysis. The final samples of new stock recommendations and new target prices are shown in table 7-1:

Table 7-1 The final sample of new recommendations and target prices for the period Jan 1997 to Dec 2002 before and after eliminating multiple recommendations

Sample	Before eliminating multiple recommendations	After eliminating multiple recommendations
New buy	3265	2232
New sell	1129	684
Increased target price	21,124	4,825
Decreased target price	17,336	4,956

The chapter is organised as follows: section 7.2 discusses the subsequent market reaction to stock recommendation changes for the sample period, during the bull and the bear markets and before and after the implementation of NASD 2711, section 7.3 discusses the market reaction to change in target price for the sample period, during the bull and the bear markets and before and after the implementation of NASD 2711, and section 7.4 shows the sub-sample of stock recommendations that have performed as expected, and those that have performed contrary to expectation over the 12 month period. Section 7.5 summarises and concludes the chapter.

7.2   Subsequent market reaction to changes in stock recommendations

In this section, I present the abnormal return performance of new stock recommendations my sample period, during the bull and the bear markets and before and after the implementation of NASD 2711. The event date is defined as the date when the recommendation is changed to a new buy and sell categories. The abnormal returns are calculated from the end of the month that the change is made.

7.2.1   Performance of stock recommendations during the sample period

Table 7-2 summarises the abnormal return performance attributable to new buy and new sell recommendations. Panel A shows that the BHAR for the new buy recommendations are driven mainly by the returns in month 0 and there is no post-recommendation drift. Thus, the mean BHAR in the month that the recommendation is changed is +5.67% (t = 13.63) and does not change significantly in the subsequent months. In month 12, the

Table 7-2 Performance of new buy and sell recommendations

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

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

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

****,***, **, and * denote significance at 0.1% 1%, 5% and 10% levels, respectively

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[10] The statistic M is defined to be $M = (N^+ - N^-)/2$ where N^+ is the number of values that are greater than Mu0 and N^- is the number of values that are less than Mu0. Values equal to Mu0 are discarded. Under the hypothesis that the population median is equal to Mu0, the sign test calculates the p-value for M using a binomial distribution. The test is based on the null hypothesis that the population median equals Mu0. The default value in SAS for Mu0 is 0.

mean abnormal return is 7.94% while the median is -4.97%. A total of 123 firms are delisted over the 12 month period of my performance evaluation.

The fact that I 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 (2005), that the value of new buy recommendations is short-lived and lasts only for one month.

Table 7-2 Panel B provides evidence of continuing negative market reaction for up to 12 months after stock recommendations are changed to the sell category. The mean BHAR in the recommendation month is -5.59% (t = 6.80) and increases to -13.61% (t = -4.65) by month 12. The median BHAR is significantly negative over the 12 month period. A total of 79 companies are delisted over the period of performance evaluation.

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 (2005), that the market reaction to negative recommendations lasts for longer (in my sample over 12 months) and is incomplete, although in their studies they observe performance over a 6 month period, whereas I assess performance over a 12 month period. The post-recommendation drift in the BHAR for new sell recommendation lends support to the idea that investors are slow in adjusting their expectations for future stock performance upon receiving new information, a behaviour which prior research proposes to explain market underreactions (e.g., Barberis et al., 1998).

7.2.2   *Differential market reaction of stock recommendations during the bull and the bear markets*

Table 7-3 shows the abnormal return performance of new buy and new sell recommendations during the bull (January 1, 1997 to March 10, 2000) and the bear (March 11, 2000 to December 31, 2002) markets. The bull and the bear markets' cut off dates are adapted from Barber et al., (2004), (see section 9.4). Both Panel A and Panel B show that in general, new buy recommendations outperform the benchmark regardless

Table 7-3 Performance of new buy recommendations during the bull and the bear markets

This table provides the buy-and-hold (BHAR) event returns for new buy recommendations during the bull market (January 1, 1997 to March 10, 2000) and the bear market (March 11, 2000 to December 31, 2002). Column 1 provides the performance period, columns 2-5 provide the mean, median, t-statistics and sign test of the BHAR for the samples of buy recommendations. Column 6 provides the number of firms existing over the 12 month horizon.

Panel A: performance of new buy recommendations during the bull market					
Period	BHAR Mean (%)	BHAR Median (%)	t-statistics	Sign test M-statistic	Live firms
Month 0	5.54	2.94	8.72****	95.5****	947
Month 1	5.82	3.14	7.10****	65.5****	943
Month 2	5.68	2.34	5.36****	37.5**	936
Month 3	6.05	1.26	4.56****	18.5	930
Month 4	5.56	0.31	3.70****	5.0	925
Month 5	5.03	-1.05	3.20****	-7.5	922
Month 6	5.43	-2.44	3.09****	-26.5*	915
Month 7	5.49	-2.89	2.63****	-36.5**	905
Month 8	5.82	-4.59	2.51*	-54.5****	902
Month 9	7.59	-6.39	2.77****	-62.5****	896
Month 10	8.78	-6.92	2.81****	-63.5****	887
Month 11	9.61	-6.58	2.77****	-56.5****	880
Month 12	15.21	-5.52	3.77****	-34.5**	872
Panel B: performance of new buy recommendations during the bear market					
Period	BHAR Mean (%)	BHAR Median (%)	t-statistics	Sign test M-statistic	Live firms
Month 0	5.77	3.82	10.34****	166.5****	1285
Month 1	5.80	3.61	8.00****	110.5****	1282
Month 2	5.28	2.51	6.39****	66.5****	1277
Month 3	4.37	1.75	4.90****	39.5**	1272
Month 4	4.07	1.00	3.91****	18.5	1263
Month 5	3.92	0.81	3.56****	23.5	1260
Month 6	3.82	0.40	3.37****	6.5	1259
Month 7	3.36	-0.86	2.78****	-17.5	1254
Month 8	2.88	-1.92	2.00**	-33.5*	1251
Month 9	3.91	-2.03	2.18*	-35.5**	1248
Month 10	3.27	-4.59	1.58	-61.5****	1245
Month 11	3.53	-4.41	1.40	-65.5****	1243
Month 12	2.59	-4.67	1.18	-69.5****	1237

****,***, **, and * denote significance at 0.1% 1%, 5% and 10% levels, respectively

Table 7-4 Performance of new sell recommendations during the bull and the bear markets

This table provides the buy-and-hold (BHAR) event returns for new sell recommendations during the bull market (January 1, 1997 to March 10, 2000) and the bear market (March 11, 2000 to December 31, 2002). Column 1 provides the performance period, columns 2-5 provide the mean, median, t-statistics and sign test of the BHAR for the samples of sell recommendations. Column 6 provides the number of firms existing over the 12 month horizon.

Period	BHAR Mean (%)	BHAR Median (%)	t-statistics	Sign test M-statistic	Live firms
Panel A: performance of new sell recommendations during the bull market					
Month 0	-8.30	-6.70	-3.64****	-14.5****	67
Month 1	-10.15	-10.09	-3.38****	-13.5****	65
Month 2	-14.30	-12.90	-3.87****	-13.5****	63
Month 3	-12.89	-7.79	-2.87****	-11.5****	62
Month 4	-15.22	-9.23	-3.47****	-10.5****	62
Month 5	-16.86	-12.55	-3.66****	-12.5****	62
Month 6	-15.28	-12.49	-3.25****	-11.5****	60
Month 7	-19.07	-20.84	-3.80****	-11.5****	59
Month 8	-20.37	-22.55	-3.60****	-11.5****	57
Month 9	-20.35	-24.22	-3.46****	-11.5****	56
Month 10	-22.73	-26.97	-3.55****	-11.5****	56
Month 11	-23.07	-25.17	-3.44****	-15.5****	54
Month 12	-23.53	-29.66	-3.15****	-14.5****	53
Panel B: performance of new sell recommendations during the bear market					
Month 0	-5.30	-4.32	-6.04****	-78.5****	617
Month 1	-6.88	-5.56	-6.99****	-91.5****	614
Month 2	-6.87	-7.56	-5.03****	-82.5****	613
Month 3	-7.61	-8.32	-5.05****	-85.5****	609
Month 4	-8.12	-8.56	-5.48****	-92.5****	605
Month 5	-9.22	-9.64	-6.23****	-98.5****	601
Month 6	-10.16	-11.24	-6.87****	-89.5****	598
Month 7	-10.95	-12.42	-6.46****	-89.5****	596
Month 8	-10.31	-15.00	-4.79****	-98.5****	589
Month 9	-11.08	-16.00	-4.58****	-107.5****	583
Month 10	-11.15	-17.92	-3.88****	-116.5****	578
Month 11	-9.66	-17.93	- 3.02****	-112.5****	574
Month 12	-12.53	-19.29	-3.99****	-120.5****	572

****,***, **, and * denote significance at 0.1% 1%, 5% and 10% levels, respectively

of the market conditions. However, the market reaction is more significant in month 0 and not on thesubsequent months. The noticeable difference between the two time periods is that, during the bull market, the 12 month mean BHAR for new buy recommendations is 15.21% (t = 3.77) whereas during the bear market, the equivalent period mean BHAR is a non-significant 2.59%.

Table 7-4 Panels A and B show that during the bull and the bear markets, sell recommendations generally underperform the benchmark as expected and during both periods the performance of sells exhibit post-recommendation drift which is more prevalent during the bull market than during the bear market. Thus, the during bull market, the 12 months mean BHAR is -23.53% (t = -3.44) which exceeds the 12 months mean BHAR during the bear market by 11 points.

7.2.3 *Market reaction of stock recommendations before and after the implementation of NASD 2711*

Table 7-5 Panels A and B present the performance of new buy recommendations before (January 1, 1997 to August 31, 2002) and after (September 1, 2002 to December 31, 2002) the implementation of NASD 2711 respectively. Month 0 mean BHAR for new buy recommendations is higher after the implementation of NASD 2711 than before, i.e., 6.94% vs. 5.60%. However, the 12 month BHARs are significantly positive (mean BHAR = 7.89%, t = 3.97) pre-NASD 2711 and positive but not significant post NASD 2711.

Table 7-6 Panels A and B show the market reaction to new sell recommendations pre and post NASD 2711. In month 0, the negative market reaction to new sell recommendations is higher by 4.13 points (7.37% vs. -3.24%) before than after the implementation of NASD 2711. The mean BHAR over the 12 months period, however, does not appear to be significantly different between the two time periods. Thus, the 12 month abnormal return is -13.25% before the implementation of NASD 2711 and -14.07% after the implementation of NASD 2711.

Table 7-5 Performance of new buy recommendations before and after the implementation of NASD 2711

This table provides the buy-and-hold (BHAR) event returns for new buy recommendations before (January 1, 1997 to August 31, 2002) and after (September 1, 2002 to December 31, 2002). Column 1 provides the performance period, columns 2-5 provide the mean, median, t-statistics and sign test of the BHAR for the samples of buy recommendations. Column 6 provides the number of firms existing over the 12 month horizon.

Panel A: performance of new buy recommendations before NASD 2711					
Period	BHAR Mean (%)	BHAR Median (%)	t-statistics	Sign test M-statistic	Live firms
Month 0	5.60	3.59	13.19****	247****	2110
Month 1	5.77	3.36	10.46****	163****	2103
Month 2	5.44	2.59	8.19****	101****	2091
Month 3	4.99	1.66	6.46****	59**	2080
Month 4	4.53	0.86	5.24****	29	2066
Month 5	4.33	0.54	4.69****	21	2060
Month 6	4.57	-0.71	4.53****	-18	2052
Month 7	4.51	-1.28	3.90****	-42*	2038
Month 8	4.19	-2.72	3.35****	-73****	2032
Month 9	5.44	-3.23	3.81****	-79****	2023
Month 10	5.41	-4.91	3.41****	-105****	2011
Month 11	5.57	-4.89	3.20****	-103****	2002
Month 12	7.89	-4.59	3.97****	-84****	1990
Panel B: performance of new buy recommendations after NASD 2711					
Period	BHAR Mean (%)	BHAR Median (%)	t-statistics	Sign test M-statistic	Live firms
Month 0	6.94	2.61	3.10****	15****	122
Month 1	6.43	3.98	2.32**	13**	122
Month 2	5.53	1.31	1.65	3	122
Month 3	6.66	-0.16	1.68	-1	122
Month 4	7.79	-0.80	1.35	-5	122
Month 5	5.47	-1.47	1.01	-5	122
Month 6	3.49	-0.89	0.71	-2	122
Month 7	0.00	-6.30	0.11	-12	121
Month 8	2.97	-8.56	0.31	-15	121
Month 9	6.12	-10.27	0.43	-19	121
Month 10	8.96	-13.83	0.51	-20	121
Month 11	15.36	-11.15	0.66	-19	121
Month 12	8.80	-12.48	0.48	-20	119

****,***, **, and * denote significance at 0.1% 1%, 5% and 10% levels, respectively

Table 7-6 Performance of new sell recommendations before and after the implementation of NASD 2711

This table provides the buy-and-hold (BHAR) event returns for new sell recommendations before (January 1, 1997 to August 31, 2002) and after (September 1, 2002 to December 31, 2002). Column 1 provides the performance period, columns 2-5 provides the mean, median, t-statistics and sign test of the BHAR for the samples of sell recommendations. Column 6 provides the number of firms existing over the 12 month horizon.

Panel A: performance of new sell recommendations before NASD 2711					
Period	BHAR Mean (%)	BHAR Median (%)	t-statistics	Sign test M-statistic	Live firms
Month 0	-7.37	-5.34	-6.23****	-67****	390
Month 1	-9.25	-6.59	-7.17****	-65****	385
Month 2	-10.06	-9.25	-5.60****	-58****	383
Month 3	-9.13	-8.67	-4.16****	-63****	379
Month 4	-9.83	-8.48	-4.87****	-60****	376
Month 5	-11.07	-9.60	-5.58****	-59****	373
Month 6	-11.17	-10.22	-6.15****	-53****	368
Month 7	-12.17	-12.22	-6.61****	-56****	366
Month 8	-12.85	-13.05	-6.15****	-59****	358
Month 9	-12.33	-14.21	-5.20****	-56****	354
Month 10	-13.20	-16.53	-5.00****	-66****	350
Month 11	-12.34	-14.36	-4.41****	-68****	345
Month 12	-13.25	-17.70	-4.22****	-70****	344
Panel B: performance of new sell recommendations after NASD 2711					
Period	BHAR Mean (%)	BHAR Median (%)	t-statistics	Sign test M-statistic	Live firms
Month 0	-3.24	-2.36	-2.99****	-26****	294
Month 1	-4.49	-4.64	-3.37****	-40****	294
Month 2	-4.33	-6.53	-2.41****	-38****	293
Month 3	-6.79	-7.56	-4.26****	-34****	292
Month 4	-7.48	-8.97	-3.97****	-43****	291
Month 5	-8.50	-10.55	-4.34****	-52****	290
Month 6	-10.01	-14.06	-4.47****	-48****	290
Month 7	-11.20	-14.89	-3.95****	-45****	289
Month 8	-9.24	-18.13	-2.43****	-51****	288
Month 9	-11.54	-19.20	-2.74****	-63****	285
Month 10	-11.08	-20.80	-2.15****	-62****	284
Month 11	-9.14	-23.87	-1.62****	-60****	283
Month 12	-14.07	-25.85	-2.61****	-65****	281

****,***, **, and * denote significance at 0.1% 1%, 5% and 10% levels, respectively

7.3 Subsequent market reaction to changes in target price

In this section, I present the abnormal return performance of changed target prices for the sample period, during the bull and the bear markets and before and after the implementation of NASD 2711. The event date is defined as the date when the target price is either increased or decreased. The abnormal returns are calculated from the end of the month in which the change is made.

7.3.1 Performance of target prices over the sample period

Table 7-7 Panel A provides performance information of stocks with increased target prices. The average BHAR for stocks with increased target prices is +6.30% (t = 18.74) in the month that the target price is changed. However, in the subsequent 12 months, the mean abnormal return drops to +3.72% (t = 3.10). From month 5 to month 12, the median is negative, suggesting that the positive impact of the increased target prices lasts only for a short time for most stocks.

Table 7-7 Panel B shows the performance of stocks with reduced target prices. In the month that the target price is decreased, the stocks underperform the benchmark by -5.12% (t = -19.10). The underperformance continues (increases) over the following months, reaching a mean of -12.50% (t = -12.99) by month 12. As with sell recommendations, the results suggest that the price reaction to unfavourable news takes much longer to be fully assimilated by the market.

Table 7-7 Performance of stocks with increased and decreased target price

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

Period	BHAR Mean (%)	BHAR Median (%)	t-statistics	Sign test M-statistic	Live firms
Panel A: Performance of stocks with increased target prices					
Month 0	6.30	3.90	18.74****	636****	4825
Month 1	6.18	3.55	16.48****	418****	4808
Month 2	5.62	2.54	12.45****	242****	4791
Month 3	5.33	1.48	9.87****	120****	4777
Month 4	4.77	0.33	8.03****	34	4746
Month 5	4.79	-0.01	7.55****	-7	4729
Month 6	5.37	-0.75	7.53****	-56	4699
Month 7	5.24	-0.16	6.34****	-97**	4666
Month 8	4.62	-2.59	5.37****	-156****	4639
Month 9	4.38	-2.50	4.78****	-142****	4616
Month 10	4.21	-3.32	4.15****	-167****	4590
Month 11	3.79	-4.99	3.41****	-204****	4558
Month 12	3.72	-5.47	3.10****	-243****	4525
Panel A: performance of stocks with decreased target prices					
Month 0	-5.12	-3.94	-19.10****	-603****	4956
Month 1	-5.79	-5.22	-17.31****	-564****	4951
Month 2	-6.45	-6.63	-16.50****	-590****	4915
Month 3	-7.14	-7.27	-16.25****	-595****	4900
Month 4	-7.96	-8.34	-16.69****	-627****	4881
Month 5	-8.73	-9.44	-16.40****	-638****	4848
Month 6	-9.17	-9.68	-16.12****	-643****	4830
Month 7	-9.90	-11.43	-16.45****	-677****	4797
Month 8	-10.82	-12.63	-16.33****	-734****	4746
Month 9	-11.05	-13.89	-15.00****	-709****	4718
Month 10	-11.45	-15.02	-13.44****	-742****	4687
Month 11	-12.43	-16.08	-14.13****	-757****	4643
Month 12	-12.50	-16.73	-12.99****	-784****	4616

****,***, **, and * denote significance at 0.1% 1%, 5% and 10% levels, respectively

7.3.2 Differential performance of stocks with increased and decreased target prices during the bull and the bear markets

Table 7-8 Panels A and B present performance of stocks during the bull and the bear markets respectively. The market reaction to increased target prices is higher in month 0 of the bear market than in month 0 of the bull market by 0.74 points. However, over the 12 month period of the bear market, the stocks with increased target price accrue a non-significant negative mean abnormal return of -0.78% whereas, over the same period the bull market mean BHAR is 7.01% (t = 3.89).

Table 7-9 Panels A and B show that market reaction to a decrease in target price is, overall, relatively similar during both the bull and the bear markets, although underperformance is generally higher during the bear market than during the bull market. Thus, in month 0, the bear market mean BHAR is -5.81% compared to -4.46% during the bull market while the 12 month abnormal return is -14.79% during the bear market compared to -10.32% during the bull market.

Table 7-8 Performance of increased target prices during the bull and the bear markets

This table provides the buy-and-hold (BHAR) event returns for increased target prices during the bull market (January 1, 1997 to March 10, 2000) and the bear market (March 11, 2000 to December 31, 2002). Column 1 provides the performance period, columns 2-5 provide the mean, median, t-statistics and sign test of the BHAR for the samples of stocks with increased target prices. Column 6 provides the number of firms existing over the 12 month horizon.

Panel A: performance of stocks with increased target prices during the bull market					
Period	BHAR Mean (%)	BHAR Median (%)	t-statistics	Sign test M-statistic	Live firms
Month 0	5.99	3.52	12.56****	353****	2832
Month 1	5.71	3.05	11.85****	227****	2823
Month 2	5.80	2.63	9.58****	145****	2815
Month 3	5.84	1.19	7.71****	56****	2806
Month 4	5.83	0.00	6.85****	0	2785
Month 5	6.18	-0.27	6.81****	-14	2772
Month 6	7.06	-0.94	6.87****	-40	2755
Month 7	7.34	-1.56	5.97****	-57**	2727
Month 8	6.94	-2.41	5.53****	-80****	2706
Month 9	6.39	-2.31	4.83****	-69****	2691
Month 10	6.79	-2.43	4.59****	-71****	2670
Month 11	6.82	-4.13	4.10****	-87****	2651
Month 12	7.01	-5.16	3.89****	-116****	2627

Panel B: performance of stocks with increased target prices during the bear market					
Period	BHAR Mean (%)	BHAR Median (%)	t-statistics	Sign test M-statistic	Live firms
Month 0	6.73	4.55	14.95****	283****	1993
Month 1	6.84	4.34	11.48****	191****	1985
Month 2	5.37	2.48	7.96****	97****	1976
Month 3	4.60	1.87	6.21****	65****	1971
Month 4	3.27	0.90	4.21****	34	1961
Month 5	2.82	0.21	3.38****	7	1957
Month 6	2.96	-0.35	3.23****	-17	1944
Month 7	2.28	-1.74	2.33****	-41*	1939
Month 8	1.33	-2.89	1.25	-75****	1933
Month 9	1.53	-2.64	1.30	-74****	1925
Month 10	0.56	-4.33	0.44	-97****	1920
Month 11	-0.30	-5.72	-0.23	-117****	1907
Month 12	-0.78	-6.10	-0.57	-128****	1898

****,***, **, and * denote significance at 0.1% 1%, 5% and 10% levels, respectively

Table 7-9 Performance of decreased target prices during the bull and the bear markets

This table provides the buy-and-hold (BHAR) event returns for decreased target prices during bull market (January 1, 1997 to March 10, 2000) and bear market (March 11, 2000 to December 31, 2002). Column 1 provides the performance period, columns 2-5 provide the mean, median, t-statistics and sign test of the BHAR for the samples of stocks with decreased target prices. Column 6 provides the number of firms existing over the 12 month horizon.

Panel A: performance of stocks with decreased target prices during the bull market					
Period	BHAR Mean (%)	BHAR Median (%)	t-statistics	Sign test M-statistic	Live firms
Month 0	-4.46	-3.78	-12.88****	-312****	2541
Month 1	-4.89	-4.42	-11.11****	-250****	2535
Month 2	-5.31	-5.47	-9.94****	-255****	2520
Month 3	-6.32	-6.61	-10.34****	-283****	2509
Month 4	-7.09	-7.85	-10.45****	-290****	2496
Month 5	-8.27	-9.08	-10.44****	-312****	2479
Month 6	-8.73	-9.80	-10.34****	-320****	2469
Month 7	-9.76	-11.27	-10.85****	-330****	2452
Month 8	-10.69	-13.20	-10.62****	-364****	2420
Month 9	-10.00	-13.90	-8.70****	-328****	2401
Month 10	-9.69	-14.85	-6.95****	-329****	2385
Month 11	-10.68	-16.32	-7.48****	-338****	2362
Month 12	-10.32	-16.36	-6.71****	-352****	2345

Panel B: performance of stocks with decreased target price during the bear market					
Period	BHAR Mean (%)	BHAR Median (%)	t-statistics	Sign test M-statistic	Live firms
Month 0	-5.81	-4.21	-14.11****	-292****	2415
Month 1	-6.73	-6.12	-13.31****	-315****	2406
Month 2	-7.66	-7.71	-13.38****	-336****	2395
Month 3	-8.01	-8.37	-12.67****	-313****	2391
Month 4	-8.88	-9.28	-13.27****	-337****	2385
Month 5	-9.20	-9.75	-13.04****	-327****	2369
Month 6	-9.64	-9.37	-12.73****	-3.23****	2361
Month 7	-10.05	-11.58	-12.65****	-347****	2345
Month 8	-10.96	-11.75	-12.85****	-371****	2326
Month 9	-12.15	-13.88	-13.40****	-371****	2317
Month 10	-13.29	-15.14	-14.05****	-414****	2302
Month 11	-14.28	-15.85	-14.24****	-420****	2281
Month 12	-14.79	-17.06	-13.09****	-433****	2271

****,***, **, and * denote significance at 0.1% 1%, 5% and 10% levels, respectively

7.3.3 Performance of stocks with increased and decreased target prices before and after the implementation of NASD 2711

Table 7-10 shows the performance of stocks with increased target prices before and after the implementation of NASD 2711. Panel A shows that there is a significant market reaction to increased target prices in month 0 (mean BHAR = 6.25% t = 17.89) and over the 12 month period (mean BHAR = 4.25%, t = 3.46) before the implementation of NASD 2711. On the other hand, after the implementation of NASD 2711, stocks with increased target prices realise significant market reaction in month 0 (mean BHAR = 6.89%, t = 5.69) but over the 12 month period the mean BHAR is negative (mean BHAR= -3.82%, t = 0.76) albeit not significant.

Table 7-11 shows the performance of stocks with decreased target prices before and after the implementation of NASD 2711. Overall, there is not a significant difference in the performance of stocks with decreased target prices before and after the implementation of NASD 2711. It is, however, noted that the market reaction to decreased target prices is higher by 2.96 points in month 0 before the implementation of NASD 2711, but over the 12 month period the underperformance is relatively higher (mean BHAR = -13.89%, t = -2.64) after the implementation of NASD 2711 than before the implementation of NASD 2711 (mean BHAR = -12.45%, t = -12.84).

Table 7-10 Performance of increased target prices before and after the implementation of NASD

This table provides the buy-and-hold (BHAR) event returns for stocks with increased target prices before (January 1, 1997 to August 31, 2002) and after (September 1, 2002 to December 31, 2002). Column 1 provides the performance period, columns 2-5 provide the mean, median, t-statistics and sign test of the BHAR for the samples of stocks with increased target price. Column 6 provides the number of firms existing over the 12 month horizon.

Panel A: performance of stocks with increased target prices before the implementation of NASD 2711					
Period	BHAR Mean (%)	BHAR Median (%)	t-statistics	Sign test M-statistic	Live firms
Month 0	6.25	3.88	17.89****	589****	4497
Month 1	6.20	3.75	16.26****	411****	4480
Month 2	5.80	2.88	12.43****	235****	4464
Month 3	5.52	1.66	9.81****	126****	4452
Month 4	4.90	0.31	7.91****	30	4423
Month 5	5.02	0.02	7.57****	3	4407
Month 6	5.72	-0.06	7.74****	42	4379
Month 7	5.56	-1.30	6.50****	-70**	4348
Month 8	4.90	-2.32	5.56****	-121****	4321
Month 9	4.66	-2.08	5.02****	-103****	4299
Month 10	4.60	-2.67	4.49****	-125****	4274
Month 11	4.24	-4.28	3.73****	-163****	4243
Month 12	4.25	-4.80	3.46****	-202****	4212

Panel B: performance of stocks with increased target price after the implementation of NASD 2711					
Period	BHAR Mean (%)	BHAR Median (%)	t-statistics	Sign test M-statistic	Live firms
Month 0	6.89	4.58	5.69****	47****	328
Month 1	5.83	0.69	3.33****	7	328
Month 2	3.12	1.16	1.76*	7	327
Month 3	2.66	-0.90	1.42	-6	325
Month 4	2.93	0.083	1.45	4	323
Month 5	1.73	-1.56	0.81	-10	322
Month 6	0.51	-3.01	0.19	-15	320
Month 7	0.87	-6.55	0.27	-27****	318
Month 8	0.81	-7.41	0.21	-30****	318
Month 9	0.07	-11.51	0.16	-39****	317
Month 10	-1.10	-11.76	-0.22	-42****	316
Month 11	-2.65	-12.27	-0.53	-42****	315
Month 12	-3.82	-15.76	-0.76	-43****	313

****,***, **, and * denote significance at 0.1% 1%, 5% and 10% levels, respectively

Table 7-11 Performance of decreased target prices before and after the implementation of NASD

This table provides the buy-and-hold (BHAR) event returns for stocks with decreased target prices before (January 1, 1997 to August 31, 2002) and after (September 1, 2002 to December 31, 2002). Column 1 provides the performance period, columns 2-5 provide the mean, median, t-statistics and sign test of the BHAR for the samples of stocks with decreased target price. Column 6 provides the number of firms existing over the 12 month horizon.

Panel A: performance of stocks with decreased target prices before the implementation of NASD 2711					
Period	BHAR Mean (%)	BHAR Median (%)	t-statistics	Sign test M-statistic	Live firms
Month 0	-5.29	-4.00	-19.09****	-585****	4672
Month 1	-5.93	-5.33	-17.28****	-5.31****	4657
Month 2	-6.60	-6.64	-16.51****	-554****	4631
Month 3	-7.29	-7.35	-16.03****	-558****	4619
Month 4	-8.02	-8.36	-16.22****	-584****	4601
Month 5	-8.79	-9.57	-15.90****	-5.95****	4568
Month 6	-9.21	-9.72	-15.61****	-600****	4550
Month 7	-9.98	-11.41	-16.17****	-632****	4518
Month 8	-10.92	-12.44	-16.25****	-676****	4469
Month 9	-11.03	-13.79	-14.78****	-638****	4445
Month 10	-11.41	-14.68	-13.12****	-687****	4416
Month 11	-12.37	-15.76	-13.81****	-703****	4375
Month 12	-12.45	-16.36	-12.84****	-732****	4348
Panel B: performance of stocks with decreased target price after the implementation of NASD 2711					
Period	BHAR Mean (%)	BHAR Median (%)	t-statistics	Sign test M-statistic	Live firms
Month 0	-2.33	-2.99	-2.22**	-18**	284
Month 1	-3.35	-4.54	-2.30**	-33****	284
Month 2	-4.04	-6.56	-2.21**	-36****	284
Month 3	-4.79	-5.79	-2.78****	-37****	281
Month 4	-6.95	-8.04	-3.95****	-43****	280
Month 5	-7.75	-8.10	-4.15****	-43****	280
Month 6	-8.65	-8.77	-4.12****	-44****	280
Month 7	-8.63	-11.73	-3.21****	-44****	279
Month 8	-9.33	-14.00	-2.73****	-58****	277
Month 9	-11.42	-16.90	-2.98****	-62****	273
Month 10	-12.53	-18.80	-3.09****	-57****	271
Month 11	-14.01	-20.05	-3.24****	-55****	268
Month 12	-13.89	-22.04	-2.64****	-53****	268

****,***, **, and * denote significance at 0.1% 1%, 5% and 10% levels, respectively

7.4   *Stocks performing contrary (according) to expectation*

The methodology employed for selecting nonconforming stocks is described in section 4.3. In this section I identify the stocks that have/have not performed as expected. In theory, a 'buy' recommendation is issued when a stock is perceived to be undervalued. Conversely, a 'sell' recommendation is issued when a stock is believed to be overvalued, while a stock awarded 'hold' is believed to be fairly priced. The definitions of stock recommendations by the top ten brokerage firms follow this same idea but go even further in specifying the actual percentages by which the stocks that are classified to each of the three categories are expected to outperform/underperform the respective industry averages. Generally, according to brokerage firms, a buy (sell) recommendation is expected to outperform (underperform) the industry benchmark by at least 10% or higher depending on risk. Appendix 1 provides detailed information on how different brokerage firms define the recommendations' ratings.

The selection of nonconforming stock recommendations in my thesis is thus based on how the stock ratings are defined by the brokerage firms. Therefore, based on the brokerage firms' definitions of stock ratings, in this research a buy recommendation is deemed to be performing contrary to analysts' expectations if the subsequent performance over the following 12 month period is at least 10% lower than that of the respective benchmark. Conversely, a sell recommendation is not conforming to analysts' expectations if the subsequent performance exceeds that of the benchmark by at least 10% over the next 12 months. In the actual analysis, however, I increase the cut-off percentage to at least 20% so that only extreme cases of non-conformance are analysed, i.e., only buys (sells) that underperform (outperform) the industry by at least -20% (+20%) are considered. The cut-of point is increased to 20% for the following reasons:

    i.   It provides me with a much cleaner test because if the analyst recommendation is associated with stock returns in line with the analyst output, then it is difficult to distinguish between bias and valid judgement. Investigating extreme cases of stocks with nonconforming subsequent stock returns is an attempt to remove analysts' correct judgemental processes.

ii.   Analysts may be biased even if the stock performance is in line with what is expected. However, I believe that potential bias may be much more directly measurable when the outturn is demonstrably wrong to a significant extent, i.e., at least 20% below or above what is expected.

iii.   Increasing the cut-off also makes the number of cases I have to work with more manageable, more so because I have to manually collect the data for some variables such as corporate relationships and target price for each stock recommendation that is found to be nonconforming. Therefore, focussing on extreme nonconforming situations is viewed as being a better way of testing my research hypotheses than using, for example, a random sample of all new buy and new sell cases.

Table 7-12 Panel A shows that 62% of all new buy recommendations earn positive returns on the month that the recommendation is changed. However, 12 months after the stocks are awarded a buy recommendation, 45% still earn a cumulative positive return, while 55% accrue a negative return. The interesting question is what percentage of these stocks actually attains at least a minimum of 10% benchmark outperformance stipulated by the brokerage firms in their definition of buy recommendations?

Panel A shows that on average, only 36% of stocks that receive a new buy status outperform the benchmark by at least 10% over the 12 month period, while 64% do not. Of the 1,220 stocks that underperform the benchmark, about 34% underperform the benchmark by -20% or more (last column) by the 12th month. These are the stocks that are of most interest in this research. The main purpose is to establish why they are awarded a buy recommendation and yet perform poorly and contrary to expectation.

Table 7-12 Panel B indicates that in the month of the recommendation change 63% of the stocks receiving sell ratings earn negative cumulative returns, while 37% earn positive returns. By the 12th month after the recommendation is changed, 70% of these

Table 7-12 Distribution of new buys/sells performance over time and selection of nonconforming stock recommendations

This table shows how stocks which received new buy/sell recommendations performed over the 12 month period after the recommendations are changed. Column 1 gives the period after the change is made. Column 2 shows the number of firms whose performance is in the expected direction. Column 3 shows the number of firms whose performance is in an unanticipated direction. Column 4 shows the number and percentage of buy/sell recommendations yielding returns of at least 10 -15% as per brokerage firms' definition of recommendations. Column 5 shows the number and percentage of recommendations with abnormal returns in the extreme opposite to the expectation i.e., below/above 10% and 20%.

Panel A: Performance of new buy recommendations over time N = 2232								
Month	No. of firms with positive return (BHAR >= 0)	No. of firms with negative return (BHAR < 0)	Expected outperformance BHAR >= 10%		Unexpected Underperformance BHAR = < -10 %		BHAR = <-20 %	
			N	%	n	%	n	%
0	1378	854	535	32.89	354	15.86	121	5.42
1	1292	940	604	36.65	495	22.17	221	9.90
2	1220	1012	662	37.05	575	25.76	321	14.38
3	1174	1058	655	35.71	659	29.52	383	17.15
4	1139	1092	662	36.78	726	32.52	446	19.98
5	1135	1097	669	36.42	832	37.27	558	25.00
6	1096	1136	689	36.38	843	37.76	550	24.64
7	1062	1170	697	36.34	881	39.47	591	26.47
8	1028	1204	697	35.89	914	40.94	643	28.80
9	1018	1214	697	35.75	922	41.30	658	29.48
10	991	1241	695	34.86	963	43.14	696	31.18
11	994	1238	701	35.08	973	43.59	749	33.55
12	991	1220	698	34.68	996	44.62	759	34.00

Panel B: Performance of new sell recommendations over time N = 684								
Month	No. of firms with negative return (BHAR < 0)	No of firms with positive return (BHAR >= 0)	Expected underperformance BHAR <= -10 %		Unexpected Outperformance BHAR > +10 %		BHAR >+20 %	
			N	%	n	%	n	%
0	435	249	225	32.89	93	13.59	44	6.43
1	447	237	286	41.81	129	18.85	68	9.94
2	438	246	312	45.61	131	19.15	75	10.96
3	439	245	317	46.35	139	20.32	83	12.13
4	445	239	331	48.39	151	22.07	87	12.71
5	440	244	349	51.02	171	25.00	130	19.00
6	443	241	368	53.80	160	23.39	108	15.78
7	443	241	373	54.53	159	23.24	102	14.91
8	452	232	375	54.82	147	21.49	103	15.05
9	461	223	388	56.73	145	21.19	102	14.91
10	470	214	391	57.16	141	20.61	109	15.93
11	470	214	393	57.46	153	22.36	120	17.54
12	477	207	401	58.63	150	21.92	111	16.22

stocks earn negative returns. About 59% of the stocks with a sell rating underperform the benchmark by at least 10%, which is the minimum percentage underperformance required by the brokerage firms to define a sell recommendation. Only 16% of these stocks outperform the benchmark by an extreme +20%.

In general terms, according to the expected underperformance/outperformance column in table 7-12, new sell recommendations perform more closely to analyst expectations than their new buy counterparts 12 months after the change in recommendation. This is further substantiated by the fact that the percentage of sell stocks outperforming by an extreme 20% is far lower than the equivalent percentage of underperformance by new buys.

7.4.1 Discussion and summary

There are two assumptions made in the performance evaluation analysis. Firstly, it is assumed that investors respond quickly and rationally to the information conveyed by analysts about changes in stock recommendations and target prices. However, this information takes a long time (i.e., possibly one year) to be fully assimilated by the market in the case of bad news (new sell recommendations and target price falls). Secondly, analysts recommend 'buy' for a stock when they feel the stock is underpriced by the market place (Stickel, 1995) and the investor would expect the market return to be above normal for that particular stock. Conversely, for the 'sell' recommendations it is expected that the investor will earn below the normal rate of return.

The empirical evidence from the analysis of changes in stock recommendations (table 7-1) suggests that during the month in which the stock recommendations are changed to a new buy or new sell category, there is a significant market reaction. These findings are consistent with the interpretation that overall, investors find analysts' changes in stock recommendations (e.g. Stickel, 1995; Womack, 1996; Ho and Harris, 1998; Barber et al., 2001 and Ryan and Taffler, 2005) particularly useful and have investment value. In the same manner, the significant market reaction to changes in target prices (table 7-7) supports the findings of Brav and Lehavy (2003) that capital market participants perceive analyst price targets as valuable. The magnitude of outperformance is higher

for increased target prices than for new buy recommendations in month 0 but over the 12 month period, the new buy recommendations accrue higher cumulative return (7.94% vs. 3.72%) than increased target prices. On the other hand, the extent of underreaction is higher for new sells than for decreased target prices in month 0 and over the 12 month period.

The stock market reacts significantly and positively to new buy recommendations and increased target prices only in the month that the recommendations or target prices are changed. Conversely, the market reacts significantly and negatively to the stocks that receive sell ratings and to the ones with decreased target prices, both in the month that the change is effected and in the subsequent months up to month 12. The market reaction to new sell and decreased target prices exhibits a post recommendation stock price drift which lasts for up to 12 months subsequent to the recommendation change. As is shown by the extant literature (e.g., Ryan and Taffler, 2005) the price reaction to new sell recommendations is greater than to new buy recommendations. On the other hand, there is no drift associated with new buy recommendations.

New buy recommendations outperform the benchmark regardless of the market condition. However, the 12 month abnormal returns are significantly higher during the bull market than during the bear market. On the other hand, sell recommendations generally underperform the benchmark as expected and during both the bull and the bear markets and the performance of sells exhibit post-recommendations drift which is more prevalent during bull market than during bear market. New buy recommendations accrue a higher return over the 12 month period prior to the implementation of NASD 2711 and not after. The abnormal returns earned by stock awarded new sell status are not significantly different before or after the implementation of NASD 2711.

The 12 month outperformance of stocks with increased target price is higher during the bull market than during the bear market. On the other hand the 12 month return for decreased target price is higher during the bear market. The 12 month abnormal return is significantly positive prior to the implementation of NASD 2711, and negative and not significant after the implementation. There is no significant change in the overall

market reaction of the market to decreased target prices either before or after the implementation of NASD 2711.

Generally, the reaction of the market to changes in stock recommendations and target prices is as expected, i.e., overall new buy recommendations and stocks with increased target prices outperform the benchmark (in the short-term), whereas sell recommendations and decreased target prices underperform the benchmark. However, in each one of these groups, there are some stocks which perform in an extreme opposite direction to the one expected.

Results show that 62% (1378) of the new buy stocks in my sample outperform the benchmark in the month that the recommendation is changed. By the 12th month, only 44% (991) have outperformed the benchmark over the 12 month period, while 56% (1,220) actually underperform the benchmark. These results show that, in general, positive returns from a change of recommendation to a new buy are short-lived and last only for a few months. Of the 56% that underperform, 34% (759) underperformed the benchmark by at least -20 % by the 12th month.

Conversely, 64% (435) of new sell recommendations underperform the benchmark in the month of the recommendation change, and that percentage increases to 70% over the 12 month period, indicating that stocks which receive a sell recommendation continue to underperform over the following 12 month period. Only 16% (111) of new sell stocks outperform the benchmark by at least +20% by month 12.

This research study aims to assess the reasons why stocks that are awarded buy (sell) ratings underperform (outperform) the relevant benchmark over the 12 month period following the recommendation change. In this chapter, I find that a large percentage of new buy recommendations do not perform as expected, while relatively few sell recommendations outperform. Barber et al., (2004) posit that at least part of the underperformance of investment bank buy recommendations is due to a reluctance by analysts to downgrade stocks whose prospects dimmed during the bear market of 2000-2002. This study goes further in seeking to establish which other factors explain this

degree of underperformance in buy recommendations and outperformance in sell recommendations. Chapter 8 explores the factors that are associated with analysts' nonconforming stock recommendations using binary logistic regression analysis.

Chapter 8 Experimental design and empirical results

8.1   Introduction

This chapter seeks to establish the factors that play a major role in influencing analysts to issue buy/sell recommendations which lack market impact, i.e., buys (sells) that underperform   (outperform)   the   benchmark.   Only   new   buys/sells underperforming/outperforming the benchmark by extreme values of 20% and above are analysed. Section 7.4 provides justification for using extreme values only.

This chapter also sets out to predict the odds/probability of analysts issuing nonconforming buy (sell) recommendations using a specified set of predictors. Given the recent findings (e.g., Brav and Lehavy, 2003) that target prices have significant information content, in a further analysis, I test whether the factors that impact on the stock ratings differ from those that affect target prices. Knowing whether the two are influenced by the same factors is important because it will enable investors to work with both signals appropriately.

The chapter is organised as follows: Section 8.2 presents the characteristics of nonconforming new buy (sell) recommendations. Section 8.3 discusses factors which differentiate between nonconforming new buy and new sell recommendations. Section 8.4 discusses the important determinants of analyst target prices and section 8.5 summarises and discusses the chapter.

8.2   Characteristics of the nonconforming buy and sell recommendations

Of the 1,220 new buy stocks that underperformed their respective benchmark, 34% (759) actually underperformed the benchmark by at least -20% by the 12th month. However, only 261 (34%) of these stocks have an accompanying research report available. On the other hand, about 207 (30%) new sell stocks outperformed their respective benchmark 12 months after the recommendations were downgraded to a sell rating. Of those, about 111 (16%) outperformed the benchmark by at least +20%. Research reports are available for only 10% of these sell recommendations and are

spread throughout the sample period. All available research reports are obtained from the *Investext plus* database.

OPTIMISM, CERTAINTY and ACTIVITY which serve as proxies for psychological biases (overconfidence and representativeness biases) are calculated from the research reports written by analysts to justify their recommendations. These textual variables are included in the analysis because in their recent study, Fogarty and Rogers (2005) argue that we can understand analysts and their work better if we do not just analyse the numerical values in their reports, but we also analyse the textual data in their reports. In their study, they conclude that analysts' stock recommendations are characterised by bias, skew and lack of science.

TGTPRCE_CHNG, a variable which measures the percentage change in the analyst projected target price and INVEST_RELATE, a variable measuring the relationship between brokerage houses and firms are also obtained from the same research reports that provide scores for OPTIMISM, CERTAINTY and ACTIVITY. If TGTPRCE_CHNG information is missing from the research reports, such information is obtained from *First Call* database. PRICE_MOM, FIRM_SIZE and BTOM values are calculated from data obtained from the *Centre for Security Prices (CRSP)* database and *Compustat* while ANALY_FOLL is taken from *IBES*.

Table 8-1 shows statistics for the main variables used in this part of the analysis. Results show that firms that are awarded new sell recommendations have smaller market capitalisation (mean FIRM_SIZE = $3,195 million) compared to their new buy counterparts (mean FIRM_SIZE = $11,816 million) with the mean difference of 94%, significant at 0.01% level. The new sell stocks generally have not performed well in the past (mean PRICE_MOM = -0.014) compared with new buys (mean PRICE_MOM = 0.018) and the mean difference between the two is 3.3%, significant at 0.01%. Not surprisingly, the target price for these new sell stocks is predicted to fall significantly (mean TGTPRCE_CHNG = -0.140). These stocks also have higher book-to-market (mean BTOM = 0.995) and as such may be classified as value stocks whereas new buys stocks have low book-to-market (mean BTOM = 0.368) and may be classified as glamour stocks. The mean number of analysts following the new sell stock (mean

ANALY_FOLL = 24) is lower than the number following new buy stocks (mean ANALY_FOLL = 29). The mean difference for analysts following nonconforming new buy recommendations and nonconforming new sell recommendations is significant at 0.01% level. As expected the language used by investment analysts to justify their research reports is significantly more optimistic for new buys than is the case for new sells. However, there is no significant difference in the language indicating CERTAINTY and ACTIVITY between the nonconforming new buy and new sell recommendations. The mean for corporate relationships (INVEST_RELATE) is higher for new buys than it is for new sells (0.95 compared to 0.73) and the mean difference is significant at 5% level.

The kurtosis for variables ACTIVITY, FIRM_SIZE and TGTPRCE_CHNG for nonconforming new buy recommendations are severely peaked compared to their nonconforming new sell recommendations equivalents. These same variables are also highly positively skewed (except ACTIVITY which is negatively skewed) compared their nonconforming new sell counterparts.

Table 8-1 Characteristics of the nonconforming new buy and new sell recommendations

The table shows statistics on the characteristics of nonconforming new buy and new sell recommendations that are issued between January 1997 and December 2002. Column 1 shows the variables and column 2-11 shows the mean, 1st quartile, median, 3rd quartile, standard deviation, kurtosis, skewness, highest and lowest extreme values and mean difference between the two samples respectively. ****, ***, **, * denote significance at 0.1%, 1%, 5% and 10% respectively.

Panel A: Underperforming new buy recommendations
N = 261

Model variables[a]	Mean	1st Quartile	Median	3rd Quartile	Standard Deviation	Kurtosis	Skewness	Extreme values		Mean difference (mean buy-mean sell)
								Lowest	Highest	
OPTIMISM	51.38	50.22	51.25	52.56	2.48	3.93	-0.26	38.46	61.35	0.843*
CERTAINTY	50.63	49.37	50.57	51.72	2.01	2.26	0.13	41.45	58.60	-0.004
ACTIVITY	47.75	47.15	48.99	50.47	6.58	51.53	-6.05	-21.29	54.88	0.792
PRICE_MOM	0.018	-0.010	0.016	0.041	0.054	2.010	0.029	-0.185	0.174	0.033****
FIRM_SIZE (log)	7.94	6.75	7.81	8.98	1.64	-0.16	0.35	3.81	12.10	0.940****
FIRM_SIZE (raw)	11,816	861	2,480	7,978	28236	19.836	4.287	45	181,286	8620****
BTOM	0.368	0.104	0.257	0.458	0.478	33.187	4.746	0.001	4.508	-0.626****
ANALY_FOLL	30	19	27	39	15	0.111	0.811	6	100	5.789****
INVEST_RELATE	0.95	0	1	2	0.77	-1.31	0.07	0	2	0.225**
TGTPRCE_CHNG	0.158	-0.069	0.057	0.200	0.588	51.198	5.768	-0.738	6.285	0.298****

Panel B: Outperforming new sell recommendations
N = 71

Model variables[a]	Mean	1st Quartile	Median	3rd Quartile	Standard Deviation	Kurtosis	Skewness	Extreme values		Mean difference (mean buy-mean sell)
								Lowest	Highest	
OPTIMISM	50.54	48.84	50.32	51.85	2.43	0.47	0.56	44.64	56.85	0.843*
CERTAINTY	50.63	49.24	50.55	51.92	2.42	4.27	1.03	45.44	61.19	-0.004
ACTIVITY	48.56	47.02	48.50	50.29	3.54	10.84	0.60	33.84	65.86	0.792
PRICE_MOM	-0.014	-0.045	-0.009	0.019	0.057	0.717	-0.058	-0.146	0.160	0.033****
FIRM_SIZE (LOG)	7.00	6.08	7.15	8.14	1.63	-0.22	-0.33	2.98	10.26	0.940****
FIRM_SIZE (RAW)	3,195	439	1,284	3,434	5,090	9.82	2.91	19.88	28,600	8620****
BTOM	0.995	0.317	0.506	0.958	1.502	10.128	3.212	0.051	7.514	-0.626****
ANALY_FOLL	24	13	24	33	13	-0.24	0.464	2	60	5.789****
INVEST_RELATE	0.73	0	1	1	0.60	-0.53	0.21	0	2	0.225**
TGTPRCE_CHNG	-0.14	-0.33	-0.16	-0.02	0.37	6.95	1.66	-0.90	1.60	0.298****

OPTIMISM$_{j,t}$ = is a content analysis (*Diction* score) variable indicating endorsement of some person, group, concept or event or highlighting their positive entailments as captured in the language used by the analyst when changing firm *j*'s stock rating. This variable serves as a proxy for analyst overconfidence;

CERTAINTY$_{j,t}$ = is a content analysis (*Diction* score) variable indicating resoluteness, inflexibility and completeness in the language used by an analyst when changing firm *j*'s stock rating. This variable serves as a proxy for analyst overconfidence;

ACTIVITY$_{j,t}$ = is the 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 analysts' representativeness bias;

PRICE_MOM$_{j,t-1}$ = is firm j's one year actual percentage change in stock price over year t computed as stock price at time t/stock price at time t-1 * 100;

FIRM_SIZE (log)$_{j,t-1}$= is firm size, 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 in million dollars;

FIRM_SIZE (raw)$_{j,t-1}$ = is firm size in million dollars, measured as a the market value of equity for firm *j* at the end of the year preceding the change of recommendation;

BTOM$_{j,t-1}$ = is firm *j*'s book value per share divided by market value of equity at the end of the year preceding the change in recommendation in million dollars;

ANALY_FOLL$_{j,t-1}$ = is the number of analysts following (for all brokerage firms available on *IBES*) the firm in the calendar year that firm *j*'s recommendation changed;

INVEST_RELATE$_{j,t}$ = is a variable that takes a value of 0 if there is no relationship between the analyst's brokerage firm and the firm, 1 if the brokerage is an underwriter of the firm or has current holdings in the firm, and 2 if the brokerage is both an underwriter and has current holdings.

TGTPRCE_CHNG$_{j,t}$ = is the percentage change in the analyst projected target price for firm j computed as [(price target at time t / price target at time t – 1 – 1]

8.3   *Factors which differentiate between nonconforming new buy and new sell recommendations*

In chapter 3, I stated seven null hypotheses. In general terms, all these hypotheses are testing whether overconfidence (as measured by *Diction* scores OPTIMISM and CERTAINTY) and representativeness bias (as measured by ACTIVITY, PRICE_MOM, FIRM_SIZE, BTOM, and TGTPRCE_CHNG) and corporate relationship between investment banks and firms have any impact on the type of nonconforming stock recommendation that analysts issue.

To determine the factors that differentiate between the nonconforming new buy and new sell recommendations, I fit a logistic regression model using the maximum likelihood estimation to estimate the model parameters (β). In this model, the dependent variable is RATING and the independent variables are CERTAINTY, ACTIVITY, PRICE_MOM, FIRM_SIZE, BTOM, TGTPRCE_CHNG INVEST_RELATE while ANALY_FOLL is a control variable. RATING is defined as the nonconforming buy or sell stock rating awarded by an analyst for firm j on the date of the recommendation change. RATING equals 1 if analysts issue new buy recommendations which underperform their respective reference portfolio benchmarks by at least -20% and 0 if new sells are issued that outperform their respective reference portfolio benchmark by at least +20%. The model is specified in equation 8-1 as follows:

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

$$= \alpha + \beta_1 \text{OPTIMISMj,t} + \beta_2 \text{CERTAINTY}_{j,t} + \beta_3 \text{ACTIVITY}_{j,t}$$

$$+ \beta_4 \text{PRICE\_MOM}_{j,t-1} + \beta_5 \text{FIRM\_SIZE}_{j,t-1} + \beta_6 \text{BTOM}_{j,t-1}$$

$$+ \beta_6 \text{TGTPRCE\_CHNG}_{j,t-1} + \beta_7 \text{ANALY\_FOLL}_{j,t}$$

$$+ \beta_8 \text{INVEST\_RELATE}_{j,t}$$

(8-1)

Table 8-2 presents the Pearson's correlation matrix for the model variables. Pearson correlations between OPTIMISM and CERTAINTY as well as between OPTIMISM and FIRM_SIZE are positive and highly significant. PRICE_MOM has a negative and highly significant relationship with BTOM and a positive and a significant relationship with TGTPRCE_CHNG. FIRM_SIZE has a negative and significant relationship with BTOM and a positive and significant relationship with ANALY_FOLL. BTOM has a negative and significant relationship with ANALY_FOLL and TGTPRCE_CHNG while the correlation between ANALY_FOLL and TGTPRCE_CHNG is positive and significant.

Table 8-2 Pearson correlation coefficients

This table presents the Pearson correlations for the following variables: OPTIMISM$_{j,t}$ = is a content analysis (*Diction* score) variable indicating endorsement of some person, group, concept or event or highlighting their positive entailments as captured in the language used by the analyst when changing firm j's stock rating. This variable serves as a proxy for analyst overconfidence; CERTAINTY$_{j,t}$ = is a content analysis (*Diction* score) variable indicating resoluteness, inflexibility and completeness in the language used by an analyst when changing firm j's stock rating. This variable serves as a proxy for analyst overconfidence; ACTIVITY$_{j,t}$ = is the 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 analysts' representativeness bias; PRICE_MOM$_{j,t-1}$ = is firm j's one year actual percentage change in stock price over year t computed as stock price at time t/stock price at time t-1 * 100; FIRM_SIZE$_{j,t-1}$= is firm size, 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 in million dollars; BTOM$_{j,t-1}$ = is firm j's book value per share divided by market value of equity at the end of the year preceding the change in recommendation in million dollars; ANALY_FOLL$_{j,t-1}$= is the number of analysts following (for all brokerage firms available on *IBES*) the firm in the calendar year that firm j's recommendation changed; INVEST_RELATE$_{j,t}$ = is a variable that takes a value of 0 if there is no relationship between the analyst's brokerage firm and the firm, 1 if the brokerage is an underwriter of the firm or has current holdings in the firm, and 2 if the brokerage is both an underwriter and has current holdings. TGTPRCE_CHNG$_{j,t}$ = is the percentage change in the analyst projected target price for firm j computed as [(price target at time t / price target at time t – 1 – 1]. P-values are listed below the correlation numbers. ****, ***, **, and * denote significance at 0.1%, 1%, 5%, and 10% levels respectively.

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	OPTIMISM	CERTAINTY	ACTIVITY	PRICE_MOM	FIRM_SIZE	BTOM	ANALY_FOLL	INVEST_RELATE	TGTPRCE_CHNG
OPTIMISM	1								
CERTAINTY	0.1366 0.0127**	1							
ACTIVITY	-0.0975 0.0758*	0.1353 0.0136**	1						
PRICE_MOM	0.0755 0.1714	0.0389 0.4817	0.0853 0.1222	1					
FIRM_SIZE	0.1239 0.0252**	-0.0059 0.9153	-0.0633 0.2542	-0.0557 0.3154	1				
BTOM	-0.1679 0.0023****	-0.0673 0.2250	0.0461 0.4061	-0.1214 0.0284**	-0.4008 0.0001****	1			
ANALY_FOLL	0.0833 0.1298	-0.0198 0.7181	-0.066 0.2262	0.0070 0.8993	0.7639 0.0001****	-0.2927 0.0001****	1		
INVEST_RELATE	0.0403 0.4639	0.0587 0.2866	0.0639 0.2458	0.0191 0.7294	0.0248 0.6549	-0.0719 0.1955	-0.0253 0.6463	1	
TGTPRCE_CHNG[11]	0.0692 0.2226	0.0702 0.2162	0.0272 0.6315	0.2451 <0.0001****	0.0585 0.3062	-0.1065 0.0622*	0.1080 0.0567**	0.0139 0.8071	1

[11] The correlation between target price (TGTPRCE_CHNG) and RATING is significant at 0.1% level.

8.3.1 *Logistic regression model 1 fitting RATING against model variables and control variable*

The primary empirical question of this study is whether psychological biases (overconfidence bias and representativeness biases) play a major role in influencing analysts to issue stock recommendations which perform contradictory to expectations in addition to corporate relationships. Table 8.3 reports the logistic regression model results. OPTIMISM is positive and significant ($p<0.10$, chi-square $= 2.75$) in explaining the type of stock rating analysts issue. This finding is inconsistent with null hypothesis $H1_0$ that the tone of language used by analysts in the research reports they prepare to justify their stock ratings is not optimistic. The significance of OPTIMISM suggests that analysts' overconfidence makes them issue stock ratings which eventually perform contradictory to expectations. The odds ratio of 1.264 indicates that the odds will increase (greater chance of buy recommendations which significantly underperform the respective benchmark) by a factor of 1.264 for every unit increase in OPTIMISM if all other variables are held constant.

Below is an example of a statement extracted from the research report with the highest OPTIMISM score. Interestingly, in this illustration, the analyst's optimism seems to be heightened by the fact that an analyst has talked to the firm's CEO. Fogarty and Rogers (2005) equate analysts' dependence on the information from the CEO to lack of science on the part of analysts:

> …….. We recently met with Chairman and CEO, A.F. Petrocelli to discuss his long-term strategy for Prime. We think a strategy is beginning to crystallize. We believe Mr. Petrocelli plans to streamline Prime, ultimately shedding both Homegate and Wellesley if it can be done at reasonable values. We believe the sale of the full-service division is the first step in that direction, Homegate and Wellesley could take a while. Prime is also in the process of marketing its Frenchman's Reef property in Saint Thomas with the goal of selling the property this year. The end game, in our view, would be a pure-play on AmeriSuites with paired down real estate holdings and a smaller balance sheet. Based on our discussions with Mr. Petrocelli, he remains committed to growing AmeriSuites. Management plans to carefully invest in very selective new development and focus most of its capital spending on seeding the AmeriSuites franchise system. Ongoing investment in AmeriSuites makes sense, in

our view, because it is a proven product from a real estate standpoint and because further unit growth should continue to boost the value of the brand. In our opinion, Mr. Petrocelli is not necessarily committed to selling the whole company if the right offer does not come along. We view "the right" offer as being somewhere in the vicinity of our 12-month price target of $15 per share. Prime has a book value of just under $12 per share. We think management is committed to doing the right thing for shareholders. Mr. Petrocelli now owns approximately 1 million shares of Prime Hospitality stock (Deutsche Bank, January 15, 1999).

The parameter estimate for price momentum (PRICE_MOM) is positive and significant at $p < 0.001$. This indicates that the probability that analysts will issue a buy recommendation that underperforms the benchmark is higher for the stocks that have performed relatively well in the past. This is because analysts prefer stocks that exhibit good previous performance (Stickel, 2000; Jegadeesh et al., 2004). This finding is inconsistent with null hypothesis $H2_0$ that the coefficient of price momentum is negative and insignificant in predicting the type of stock recommendation that analyst issues. The fact that analysts use stocks' past performance as being representative of stocks' future performance is indicative of analysts' representativeness bias.

The parameter estimates for FIRM_SIZE is positive and significant at $p < 0.05$, suggesting that the larger the firm the more the likelihood that analysts will issue a nonconforming buy recommendation on the stock, either because analysts associate size of the firm with good performance or because there are other benefits that analysts derive when they issue buy ratings on large market capitalisation stocks. The size effect is well documented in the literature in terms of explaining abnormal returns. But these results show that size is also essential in explaining the analysts' nonconforming buy and sell recommendations. The odds ratio shows that an increase in the size of the firm by one unit increases the probability of analyst issuing a nonconforming new buy recommendation by a factor of 2. This finding is inconsistent with null hypothesis $H4_0$ that the size of the firm does not have any significant impact on the type of stock recommendation that analysts issue on the stock. This finding therefore supports the idea that analysts see FIRM_SIZE as representative (representativeness bias) of stocks' future performance.

Table 8-3 Determinants of new buy/sell recommendations using all model variables and control variables

This table presents the logit regression on all model and control variables. The logit regression is as shown in Eq.(8-1). The dependent variable is the stock rating. For each variable included in Eq.(8-1) the predicted sign, coefficient estimate, Wald Chi-square and odds ratio (EXP (B)) are presented in columns 2-5 respectively. R-Square, likelihood ratio and number of observations the regression is provided below the variables.

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

Note: The Wald statistics are distributed Chi-square with 1 degree of freedom

****,***, **, and * denote significance at 0.1% 1%, 5% and 10% levels, respectively

The parameter estimate for BTOM is negative as expected and significant at P<0.01. This result suggests that buy recommendations which lack appropriate market impact are generally glamour stocks. The chances of obtaining a nonconforming buy recommendation decreases when book-to-market increases. This finding is inconsistent with null hypothesis $H5_0$ that the firm's book-to-market does not have any significant impact on the type of stock recommendation that analysts issue on the stock. Also, this finding implies that, according to financial analysts, book-to market is representative of future performance of the stock.

The parameter estimate for TGTPRCE_CHNG is statistically significant at p<0.001 which suggests that there is a strong relationship between target price and the type of recommendation that analysts issue on the stock. Thus, when the target price on a stock increases (decreases) then the probability (odd ratio = 20.790) that analysts will issue a nonconforming buy (sell) recommendation increases. Although the role of the target

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price is not clear, particularly when issued together with stock recommendations, from this result, the conjecture is that financial analysts view target prices as being representative of what type of stock recommendations to issue. The finding is inconsistent with null hypothesis $H6_0$ that target price is not significantly important in predicting whether analysts will issue stock recommendations that lack market impact.

INVEST_RELATE looks at whether a corporate finance relationship between investment bank and firm has any bearing on the type of recommendation that analysts issue. The parameter estimate for INVEST_RELATE is positive, as expected, and significant at $p< 0.01$. These results are consistent with Lin and McNichols (1998), Michaely and Womack (1999), Barber et al., (2004) and Cliff (2004) that analysts' tend to issue more favourable recommendations on the stocks of firms with which their employer investment banks have a relationship. The probability that analysts will issue a nonconforming buy recommendation if there is a corporate finance relationship between brokerage house and firm is 2.89. Thus, the existing relationship between brokerage house and firm has a significant impact on the type of recommendation that analysts issue.

The log-likelihood ratio chi-square which is aimed at testing the joint effect of all model variables is 64.573, significant at $p<0.001$ suggesting that the model variables as a group play a significant role in the type of stock recommendation that analysts issue, particularly in differentiating buy and sell recommendations that do not perform as expected. The significant log-likelihood ratio chi-square suggests a significant logistic model.

Table 8-3 presents logistic regression results when target price is excluded as an independent variable. The log-likelihood ratio chi-square of 5.883 (p = 0.1%) shows that even without target price, the model variables as a group still play a significant role in the type of stock recommendation that financial analysts issue. When target price is excluded from the model, however, OPTIMISM is the only variable that becomes insignificant while all the other variables that are significant in the previous model still

Table 8-4 Determinants of new buy/sell recommendations using model variables (excluding target price) and control variables

This table presents the logit regression on model variables (excluding target price) and control variables. The logit regression is as shown in Eq.(8-1). The dependent variable is the stock rating. For each variable included in Eq.(8-1) the predicted sign, coefficient estimate, Wald Chi-square and odds ratio (EXP (B)) are presented in column 2-5 respectively. R-Square, likelihood ratio and number of observations the regression is provided below the variables.

Independent variable	Predicted sign for buys	Parameter Estimates	Wald Chi-Square	EXP (B)
Intercept	?	-1.398	0.092	-
OPTIMISM	+	0.085	1.941	1.089
CERTAINTY	+	-0.032	0.218	0.968
ACTIVITY	-	-0.045	1.471	0.956
PRICE_MOM	+	12.843	18.878****	>999.999
FIRM_SIZE	+	0.311	3.935**	1.366
BTOM	-	-0.734	7.073****	0.480
ANALY_FOLL	+	-0.005	0.104	0.995
INVEST_RELATE	+	0.426	3.990**	1.532
R^2	17%			
Likelihood ratio Chi-square	58.83****			
N	332			

Note: The Wald statistics are distributed chi-square with 1 degree of freedom

****,***, **, and * denote significance at 0.1% 1%, 5% and 10% levels, respectively

remain significant. It could be argued that OPTIMISM becomes insignificant when target price is taken out of the model because target price elevates the optimism in the language that analysts write to justify their recommendations.

8.4   *Can the important determinants of stock ratings help us explain target prices as well?*

Because of the strong positive relationship that exists between stock ratings and target prices, and the fact that two signals are often used together, I set out to test whether the same factors that explain nonconforming buy (sell) recommendations are also significant determinants of analysts' target prices issued concurrently with these stock ratings. I fit the ordinary least squares (OLS) regression model where TGTPRCE_CHNG is a dependent variable and OPTIMISM, CERTAINTY, ACTIVITY, PRICE_MOM, FIRM_SIZE, BTOM, ANALY_FOLL, INVEST_RELATE

and RATING are independent variables. ANALY_FOLL is a control variable. The model is specified in equation 8-2 as follows:

$$TGTPRCE\_CHNG = \alpha + \beta_1 OPTIMISM_{j,t} + \beta_2 CERTAINTY_{j,t} + \beta_3 ACTIVITY_{j,t}$$
$$+ \beta_4 PRICE\_MOM_{j,t-1} + \beta_5 FIRM\_SIZE_{j,t-1} + \beta_6 BTOM_{j,t-1}$$
$$+ \beta_7 ANALY\_FOLL_{j,t} + \beta_8 INVEST\_RELATE_{j,t} + RATING$$

$$(8-2)$$

All the variables in equation 8-2 are defined as in equation 8-1. Table 8-5 presents my OLS results when TGTPRCE_CHNG is a dependent variable. The results show that PRICE_MOM is positive and statistically significant ($t = 4.24$, $p<0.001$). This finding indicates that the estimation of the stocks' target price is highly influenced by the previous performance of the stock just as in the case of the stock rating. That is, firms that have performed well in the past obtain increased target prices and vice versa. This finding is interpreted as showing that previous stock performance is viewed as being representative (representativeness bias) of what the stocks' target price should be.

Not surprisingly, RATING, which is a dummy variable measuring the type of recommendation an analyst issues is significant ($t = 2.27$, $p<0.05$). This result indicates that there is a strong relationship between target price and stock recommendations and that in this sample, target prices serve to justify the stock recommendations that financial analysts issue (Bradshaw 2002). The rest of the variables in this model are insignificant.

The fact that INVEST_ RELATE is significant in predicting the type of stock recommendations and not significant in predicting TGTPRCE_CHNG may be interpreted as suggesting that stock recommendations may be related to the investment baking relationships whereas the analysts' true view resides in the target price which can't be readily interpreted by the finance director. The total variance explained (R-square) is 10%.

Table 8-5 Determination of factors which influence target prices

This table presents the ordinary least squares multiple regression results. The dependent variable is TGR_REV and all other model variables and control variables are independent variables. For each variable included in Eq.(8-2) the predicted sign, coefficient estimate and t-statistics are presented in columns 2-4 respectively. R-square and number of observations in the regression are provided below the variables.

Independent variable	Predicted sign for buys	Parameter Estimates	t-statistics
Intercept	?	-1.183	-1.20
OPTIMISM	+	0.005	0.43
CERTAINTY	+	0.015	1.00
ACTIVITY	-	0.002	0.49
PRICE_MOM	+	2.100	3.48****
FIRM_SIZE	+	-0.021	-0.72
BTOM	-	-0.040	-0.81
INVEST_RELATE	+	-0.004	-0.11
RATING[12]	+	0.191	2.27**
ANAL_FOLL	+	0.004	1.47
R^2	10%		
N=	332		

****,***, **, and * denote significance at 0.1% 1%, 5% and 10% levels, respectively

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[12] When RATING is excluded from the model. PRICE_MOM becomes the only significant variable in predicting target price

8.5   *Summary of results and discussion*

In this chapter, I set out to predict the factors that may be influencing investment analysts to issue stock ratings (buy/sell) which are associated with significantly contradictory performance. This is done by fitting a logistic regression model where RATING in a dependent variable and OPTIMISM, CERTAINTY, ACTIVITY, PRICE_MOM, FIRM_SIZE, BTOM, TGTPRCE_CHNG and INVEST_RELATE are independent variables. ANALY_FOLL is the only control variable in the model.

The model shows that OPTIMISM, PRICE_MOM, FIRM_SIZE, BTOM, TGTPRCE_CHNG and INVEST_RELATE are individually statistically significant in explaining the nonconforming buy (sell) recommendations. The results show that an increase in OPTIMISM increases the chance of analysts issuing new buy recommendations for stocks which subsequently underperform their respective benchmarks. The results suggest that analysts believe they have superior investment abilities and tend to overestimate the likely performance of the stocks they follow. Various studies such as Odean (1998b); Barber and Odean (2001) have attested to investors' overconfidence. I provide some evidence of analyst behaviour consistent with this.

The previous performance of the firm is very important in influencing analysts' stock ratings. When momentum is increased slightly, the chance of having a buy recommendation which underperforms the benchmark increases hugely. This finding is consistent with the existing literature in that analysts have incentives to give buy recommendations to stocks with recent positive relative price momentum and good financial characteristics following from documented momentum pricing anomalies and because they are actionable ideas that generate trading commissions (Stickel, 2000). Analysts appear to associate good previous stock performance with good future stock performance and vice versa. Thus analysts have representativeness bias because they view the past is being representative of the future.

Cateris paribus, larger market capitalisation stocks have a higher probability of being issued with buy recommendations which eventually underperform their respective

benchmarks. This indicates that analysts associate larger firms with positive recommendations and smaller firms with negative recommendations (representativeness bias). It may also be possible that there are other benefits that analysts derive when they issue a buy rating on large market capitalisation stocks.

Buy recommendations which lack appropriate market impact are generally glamour stocks. This results show that analysts associate firms which have high growth rate with good performance. Using the growth status of the company for making a decision about the type of recommendation to issue is another example of analysts' representativeness bias.

As is expected, the variable measuring the relationship between the brokerage firm and the company is important in determining the type of recommendation issued. Thus, companies which have some corporate finance relation with the investment bank are more likely to receive nonconforming buy recommendations. These results confirm the concern that analysts make "buy" and "strong buy" recommendations for stocks which were not necessarily undervalued but were recommended because their investment bank employers were seeking profitable corporate finance relationships with them. Analysts would also be rewarded for their part in promoting these deals via additional compensation (Financial Times, April 10, 2002).

As is documented in the literature, there is a close link between stock ratings and target prices. It is therefore, not surprising that an associated increase in target price significantly increases the likelihood of analysts issuing underperforming new buy recommendations. This strong relationship between target price and stock recommendation supports the suggestion by Bradshaw (2002) that target prices that are issued concurrent with stock recommendations serve to justify the type of recommendation that the analyst issues. Thus target price is representative of the type of stock recommendation that analysts issue.

In a further analysis, I test whether the same factors that are posited to explain nonconforming buy (sell) recommendations also drive the target price. The results show

that previous firm performance (PRICE_MOM) and the type of stock recommendation issues (RATING) are important factors in explaining the target prices. These results, again, provide me with a classic example of analysts' representativeness bias. Thus, their decision to increase or decrease the target price is dependent on the previous performance of the firm and on what the analysts perceive as the appropriate stock rating. When RATING is excluded from the model, PRICE_MOM remains the only significant variable in explaining target prices.

In summary, this chapter shows that the factors that differentiate between nonconforming new buy and new sell recommendations are optimism (OPTIMISM), momentum (PRICE_MOM), market capitalisation (FIRM_SIZE), book-to-market (BTOM), target price (TGTPRCE_CHNG) and the existing relationship between the firm and its employer brokerage firm (INVEST_RELATE). Optimism serves as a proxy for psychological bias - overconfidence. Overconfidence is defined as overestimating what one can do compared to what objective circumstances would warrant. The other five factors are meant to measure representativeness bias and the results support the hypotheses that analysts' nonconforming stock recommendations are dependent on the previous stock performance, on the size of the firm, on the firm's book-to-market, on the current target price level and on the relationship between the brokerage house and the firm.

The results also show that there is a close link between target price and the type of rating that analysts award to stocks. The results are interpreted as showing that target prices serve to justify the type of stock recommendations that analysts issue. But on the other hand, the role of target prices may be viewed as a way for analysts to ameliorate the effects of their overly optimistic reports, or part of the sales hype used to peddle stocks (Asquith, et al., 2005). This is more so because the findings of other authors like Cornel (2001) and Bradshaw (2004) suggest that change in analyst recommendations does not seem to depend on valuation models.

In general terms this chapter shows that in as far as nonconforming stock recommendations are concerned, investors tend to recognise the analysts' conflicts of

interest as well as other factors that may be influencing their stock recommendations and rationally discount their opinions. Thus, investors do not necessarily take analysts recommendations at face value as presumed by the Global Settlement (Agrawal and Chen, 2005), hence the observed performance which is contrary to the one expected.

In the next chapter, I carry-out additional test of analysts' representativeness bias over the sample period and in different sub-periods using a larger sample size compared to the sample size used in this chapter.

Chapter 9 Further tests

9.1 Introduction

In the previous chapter, I confirmed the important factors that differentiate between nonconforming new buy and new sell recommendations using both report-based (OPTIMISM, CERTAINTY, ACTIVITY, TGTPRCE_CHNG and INVEST_RELATE) and market-based factors (PRICE MOM, FIRM_SIZE, BTOM and ANALY_FOLL). In this chapter I carry out further tests of my underlying hypotheses relating to analysts' representativeness bias but using momentum, size and book-to-market only (null hypotheses 3, 4 and 5 respectively in chapter 3). Looking at the effect of only these factors and excluding other factors, particularly INVEST_RELATE, enables me to establish whether authorities are addressing the real issues by passing laws and implementing regulations which address the problem of bias arising from corporate finance relationships between firms and investment banks, or should they also look into the problem of analysts' psychological bias which, may, in fact, be difficult to regulate. The chapter investigates analysts' representativeness bias underlying analysts' nonconforming recommendations in the whole sample period, during the bull and the bear markets, and before and after the implementations of Rule NASD 2711.

In chapter 8, the samples of new buy (sell) recommendations consist only of underperforming new buys and outperforming new sells for which analysts' research reports are available from the *IBES* database. In this chapter, my samples consist of all new buy stocks which underperform the relevant benchmarks by at least <-20% and all new sell stocks that outperform the relevant benchmarks by at least >+20%. Because there is no restriction imposed by the availability of analysts' research reports, my samples are larger, i.e., 1,349 new buys and 429 new sells, compared to the samples in the previous chapter.

The chapter is organised as follows: Section 9.2 discusses the characteristics of all conforming and nonconforming new buy and new sell recommendations. Section 9.3 presents the important factors differentiating groups of conforming and nonconforming new buy and new sell recommendations. Section 9.4 discusses the important factors differentiating groups of conforming and nonconforming of new buy and new sell

recommendations during the bull and the bear markets as well as before and after the implementation of NASD 2711. Section 9.5 summarises and concludes the chapter.

9.2 Characteristics of samples of nonconforming new buy and sell recommendations

Table 9-1 presents descriptive statistics for the complete samples of nonconforming new buy (sell) recommendations. The underperforming new buy recommendations generally performed better in the past (mean PRICE_MOM = 0.011) compared to outperforming new sell recommendations (mean PRICE_MOM = -0.013) with the mean difference significant at the 0.1% level. Also, the underperforming new buy recommendations have larger market capitalisation (mean FIRM_SIZE = \$9,388 million), have a lower book-to-market (mean BTOM = 0.484) and have a stronger analyst following base (mean ANALY_FOLL = 30.065) compared to their sell counterparts whose mean FIRM_SIZE = \$5,276 million, mean BTOM = 0.827 and mean ANALY_FOLL = 26.526. The mean difference for all the variables is significant at the 0.1% level. In summary, underperforming buy stocks have most of the characteristics that the extant finance literature (e.g., Stickel, 2000) argues are associated with investment analysts awarding a buy rating to stock.

9.3 Important factors differentiating nonconforming new buy and new sell recommendations

In this section, I use a logit model approach to predict which measures of representativeness bias are significant in differentiating between nonconforming new buy and new sell recommendations. I fit a logit model which regresses the independent variables momentum (PRICE_MOM), size (FIRM_SIZE), book-to-market (BTOM), and analyst's following (ANALY_FOLL) against the dependent variable RATING. ANALY_FOLL serves as a control variable. RATING equals 1 if an analyst issues a new buy recommendation which subsequently underperforms the benchmark by <- 20% and 0 if a new sell recommendation outperforms the benchmark by >+20%.

Table 9-1 Characteristics of the conforming (nonconforming) buy recommendations

The table shows statistics on characteristics of conforming (nonconforming) buy and sell recommendations that are issued between January 1, 1997 and December 31, 2002. Column 1 shows the variables and columns 2- 9 show the mean, 1st quartile, median , 3rd quartile, standard deviation, kurtosis, skewness, extreme values and mean difference of conforming and nonconforming new buy and new sell stocks.

Panel A: characteristics of nonconforming (underperforming) new buy recommendations N = 1,349

Model Variables	Mean 1(a)	1st quartile	Median	3rd quartile	Standard Deviation	Kurtosis	Skewness	Extreme values Lowest	Highest	Mean difference 1(a)-1(b)
PRICE_MOM	0.011	-0.018	0.009	0.037	0.055	3.643	0.617	-0.190	0.3424	0.024****
FIRM_SIZE (log)	7.659	6.502	7.523	8.616	1.636	0.017	0.373	3.612	12.747	0.412****
FIRM_SIZE (raw)	9,388	666	1,851	5,522	26,294	48.871	6.107	37.064	342,558	4,112****
BTOM	0.484	0.134	0.309	0.579	0.680	34.425	4.963	0.001	7.266	-0.343****
ANALY_FOLL	30.065	19.000	28.000	39.00	15.412	0.478	0.772	2	88	3.538****

Panel B: Panel B: Characteristics of nonconforming (outperforming) new sell recommendations N = 429

Model Variables	Mean 1(b)	1st quartile	Median	3rd quartile	Standard Deviation	Kurtosis	Skewness	Extreme values Lowest	highest	Mean difference 1(a)-1(b)
PRICE_MOM	-0.013	-0.042	-0.008	0.015	0.054	1.5263	0.030	-0.190	0.204	0.024*****
FIRM_SIZE (log)	7.247	6.311	7.111	8.206	1.581	0.072	0.2144	2.989	11.996	0.412****
FIRM_SIZE (raw)	5,276	550	1,225	3,666	13,886	60.762	6.792	19.881	162,224	4,112****
BTOM	0.827	0.224	0.456	0.792	1.352	35.877	5.118	0.017	14.236	-0.343****
ANALY_FOLL	26.526	15.000	25.000	34.000	14.435	0.740	0.872	2	84	3.538****

****, ***, **, and * denote significance at 0.1%, 1%, 5%, and 10% levels respectively.

PRICE_MOM = is firm j's one year actual change in stock price at time t computed as [stock price at time t /stock price at time t-1) * 100];

FIRM_SIZE (log)$_{j,t-1}$ = is firm size in million dollars, measured using the natural logarithm of the market value of equity for firm j at the end of the year preceding the change of recommendation;

FIRM_SIZE (raw)$_{j,t-1}$ = is firm size in million dollars, measured as a the market value of equity for firm j at the end of the year preceding the change of recommendation;

BTOM$_{j,t-1}$= is firm j's book value per share divided by market value of equity at the end of the year preceding the change in recommendation;

ANALY_FOLL$_{j,t-1}$ = is the number of analysts following (for all brokerage firms available on IBES) the firm in the year that firm j's recommendation are changed change in recommendation.

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The following is the logistic regression model fitted:

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

$$= \alpha + \beta_1 \text{PRICE\_MOM}_{j,t-1} + \beta_2 \text{FIRM\_SIZE}_{j,t-1}$$

$$+ \beta_3 \text{BTOM}_{j,t-1} + \beta_4 \text{ANALY\_FOLL}_j + \varepsilon_{j,t}$$

(9-1)

where PRICE_MOM, FIRM_SIZE, BTOM and ANALY_FOLL are independent variables for firm j, $\beta_1 \ldots\ldots \beta_4$ are the regression parameter estimates and $\varepsilon_{j,t}$ is the error term. Independent variables PRICE_MOM, FIRM_SIZE, BTOM and ANALY_FOLL included in the above model are as defined in section 8-2, table 8-1. The dependent variable RATING is a dummy variable indicating nonconforming new buy (sell) recommendations.

Tables 9-2 reports the results of running the logit model for nonconforming new buy and new sell recommendations for the whole sample period. The results show that PRICE_MOM and BTOM are the two measures of representativeness bias which are individually significant in differentiating between new buy underperformers and new sell outperformers. The parameter estimates for PRICE_MOM and BTOM are 8.223 and -0.290 respectively. Both are significant at p<0.1%. The significance of PRICE_MOM and BTOM is interpreted as indicating that the previous performance of the firm and firm's growth status are viewed by analysts as being representative (representativeness bias) of what the future performance of the firm should be. The control variable ANALY_FOLL is also highly significant (p<0.1%) in predicting analysts' nonconforming ratings which suggests that over the sample period, the number of analysts following the firm is also essential in predicting analysts' nonconforming stock recommendations. Theoretically, ANALY_FOLL is linked to the size of the firm in that the larger the firm the more analysts there are following the firm's stock.

Table 9-2   Factors that differentiate between nonconforming new buy and new sell recommendations

This table presents the logit regression on the important factors which differentiate between nonconforming new buy (sell recommendations. For each variable, the predicted sign, coefficient estimate, Wald Chi-square and odds ratio (EXP (B)) are presented in columns 2-5 respectively. R-Square, likelihood ratio and number of observations in the regression is provided below the variables. The dependent variable RATING is a dummy variable that takes the value of 1 if the recommendation is an underperforming new buy and 0 if the recommendation is an outperforming new sell recommendation. The independent variables are as shown in Eq. (9-2)

Independent variable[a]	Predicted sign outperforming buys	Parameter Estimates	Wald Chi-square	EXP (B)
Intercept	?	0.818	6.169****	-
PRICE_MOM	+	8.223	54.623****	>999.999
FIRM_SIZE	+	0.031	0.358	1.031
BTOM	-	-0.290	17.509****	0.748
ANALY_FOLL	+	0.010	3.500****	1.010
R^2	6%			
Likelihood ratio Chi-square	109.08****			
N	1,778			

Note: The Wald statistics are distributed Chi-square with 1 degree of freedom

****,***, **, and * denote significance at 0.1% 1%, 5% and 10% levels, respectively

9.4   Factors differentiating between conforming and nonconforming buy (sell) recommendations during the bull and the bear markets

The sample period in this study spans two market conditions which are the bull (January 1, 1997 to March 10, 2000) and the bear (11th March 2000 to 31st December 2002). The bull market is defined as a period when the market experiences a steady increase in stock prices and the bear market is when there is a steep market decline. The cut-off dates for the bull and the bear dates are adapted from Barber et al., (2004). Both these conditions have characteristics that may influence the way analysts do their job and the type of recommendations they issue on stocks. It is, therefore, interesting to establish which measures of representativeness bias influence analysts' decision-making in the two different time periods. Generally the bull market is characterised by increasing stock prices and flourishing economy while during the bear market prices are expected to drop and the economy is by and large gloomy for investing.

Table 9-3 Factors influencing the issuance of nonconforming buy and sell recommendations during bear and bull markets

This table presents the logit regression on the important market factors which differentiate between nonconforming new buy (sell) recommendations in different market conditions. The variables are as defined in chapter 6, section 6.2. For each variable, the predicted sign, coefficient estimate, Wald Chi-square and odds ratio (EXP (B)) are presented in columns 2-5 respectively. R-Square, likelihood ratio and number of observations in the regression is provided below the variables.

PANEL A: Factors influencing nonconforming stock recommendations during bull market				
Independent variable	Predicted sign outperforming buys	Parameter Estimates	Wald Chi-square	EXP (B)
Intercept	?	3.038	12.414****	-
PRICE_MOM	+	8.484	5.566****	>999.999
FIRM_SIZE	+	-0.120	0.889	0.886
BTOM	-	-0.313	2.067	0.731
ANALY_FOLL	+	0.021	2.320	1.022
R^2	2%			
Likelihood ratio Chi-square-	13.551****			
N	664			
PANEL B: Factors influencing nonconforming stock recommendations during bear market				
Independent variable	Predicted sign outperforming buys	Parameter Estimates	Wald Chi-square	EXP (B)
Intercept	?	-0.522	1.717	-
PRICE_MOM	+	7.235	35.491****	>999.999
FIRM_SIZE	+	0.151	5.620****	1.163
BTOM	-	-0.185	6.142****	0.831
ANALY_FOLL	+	0.006	0.876	1.006
R^2	6%			
Likelihood ratio Chi-square-	76.511****			
N	1,114			

Note: The Wald statistics are distributed Chi-square with 1 degree of freedom

****,***, **, and * denote significance at 0.1% 1%, 5% and 10% levels, respectively

Table 9-3 Panel A shows that during the bull period, the only measure of representativeness bias which plays a significant role in influencing analysts to issue nonconforming stock recommendations is PRICE_MOM. The parameter estimate for PRICE_MOM is positive and significant at p<0.1% indicating that analysts' recommendations are largely biased by the previous price performance of the stock during the bull market. Thus, they regard the previous good price performance of stocks

as representative of the good future performance and the reverse is true for previous poor performers.

Table 9-3 Panel B shows that during the bear market, all the three measures of representativeness bias, PRICE_MOM, FIRM_SIZE and BTOM are individually significant at $p<0.1\%$ in influencing analysts' decision to issue nonconforming recommendations. It may be that, because of the state of affairs in the bear market, analysts tend not to rely only on the previous price performance of the firm, as is the case during the bull market but tend to also believe that the firm's market capitalisation and growth status are representative of what the future performance of the stock is likely to be.

9.5 Which factors influenced the type of stock rating before and after the implementation of NASD 2711?

In the recent past there has been concern by Congress and security regulators that analysts' recommendations do not reflect their true beliefs. Rather, it was believed that the recommendations are intended to attract and retain investment banking business (Barber et al., 2004). In order to regulate the provision of research, the National Association of Securities Dealers (NASD) proposed Rule 2711, *Research Analysts and Research Reports*. This rule was implemented on September 9, 2002. This subsection sets out to test which factors differentiate between nonconforming stock recommendations before and after the implementation of NASD 2711.

Table 9-4 Panel A shows that pre-NASD 2711 the issuance of nonconforming new buy and new sell recommendations is influenced by the firm's previous price performance (PRICE_MOM) and the growth status of the firm (BTOM). The coefficient for PRICE_MOM is positive and significant at $p<0.1\%$ indicating that pre-NASD 2711 underperforming new buys have performed well in the past and outperforming new sells have performed poorly in the past. Firms that are awarded a buy rating and perform contrary to expectation are also glamour stocks while those that are awarded a sell rating are value stocks.

Table 9-4 Factors influencing the issuance of nonconforming buy and sell recommendations before and after the implementation of NASD 2711

This table presents the logit regression on the important market factors which differentiate between nonconforming new buy (sell) recommendations before and after the implementation of NASD 2711. The variables are as defined in chapter 6 section 6.2. For each variable, the predicted sign, coefficient estimate, Wald Chi-square and odds ratio (EXP (B)) are presented in columns 2-5 respectively. R-Square, likelihood ratio and number of observations in the regression is provided below the variables.

PANEL A: Factors affecting nonconforming recommendations issued before the implementation of NASD 2711				
Independent variable	Predicted sign outperforming buys	Parameter Estimates	Wald Chi-square	EXP (B)
Intercept	?	1.860	21.254****	-
PRICE_MOM	+	8.142	35.562****	>999.999
FIRM_SIZE	+	-0.016	0.069	0.984
BTOM	-	-0.343	20.049****	0.710
ANALY_FOLL	+	0.004	0.586	1.005
R^2	5%			
Likelihood ratio Chi-square-	74.248****			
N	1,536			

PANEL B: Factors affecting nonconforming recommendations issued before the implementation of NASD 2711

Independent variable	Predicted sign outperforming buys	Parameter Estimates	Wald Chi-square	EXP (B)
Intercept	?	-4.018	14.650****	-
PRICE_MOM	+	6.021	2.994*	412.009
FIRM_SIZE	+	0.333	4.092**	1.396
BTOM	-	-0.057	0.042	0.944
ANALY_FOLL	+	0.015	0.787	1.016
R^2	9%			
Likelihood ratio Chi-square-	23.95****			
N	242			

Note: The Wald statistics are distributed Chi-square with 1 degree of freedom

****,***, **, and * denote significance at 0.1% 1%, 5% and 10% levels, respectively

Table 9-4 Panel B shows that post-NASD 2711, previous firm performance is still important in predicting analysts' nonconforming recommendations together with firm market capitalisation, as opposed to firm growth status as was the case pre-NASD 2711. The coefficients for PRICE_MOM and FIRM_SIZE are positive and significant at $p<0.1\%$ indicating that after the implementation of NASD 2711, analysts view

momentum and the size of the firm as being representative of what the stock's future performance will be.

What is interesting between the two time periods (pre and post Rule NASD 2711) is that the magnitude of the significance of PRICE_MOM is higher pre-NASD 2711 ($p<0.1\%$) and lower post-NASD 2711 ($p<10\%$). This is interpreted as indicating that Rule NASD 2711 may have reduced but not obliterated analysts' representativeness bias as measured by PRICE_MOM by requiring analysts, among other things, to disclose the percentages in their recommendations that are buys, holds and sells. Although analysts' bias is accentuated by FIRM_SIZE post-NASD 2711 as opposed to BTOM, as was the case pre-NASD 2711, it seems the significance of the reliance on the size of the firm is not very high compared to how significant book-to-market was pre-NASD 2711. Based on this, I conclude that although Rule NASD 2711 is meant to address the problems created by the relationships between investment banks and firms, it may also have helped to reduce analyst psychological bias which appears to be playing an important role in analysts' investment decisions.

9.6   Discussion and summary

Hypothetically, I expect stocks that are awarded a buy rating to outperform the appropriate benchmarks and the stocks that are awarded sell rating to underperform the appropriate benchmark. However, in practice, and as shown by the evidence in my samples of new buy and new sell recommendations, there is a large percentage of stocks that perform in an extremely opposite direction to the one analysts expect. While there may be different reasons for this, in this chapter I aim at highlighting the fact that it is not only because of the corporate finance relationships that investment banks have with firms, but also because of psychological biases (representativeness bias in particular) as measured by stocks' previous price performance, stocks' market capitalisation and firms' growth status.

The descriptive statistics show that stocks that are awarded buy rating but subsequently underperform the benchmark are those that have more positive previous price momentum, have larger market capitalisation, have lower book-to-market (i.e., are

glamour stocks) and have more analysts following compared to stocks that are awarded a sell rating and subsequently outperform their respective benchmarks. The mean difference between all the characteristics of the underperforming buys and outperforming sells is significant at the 0.1% level.

Univariate statistics, therefore, show analysts issue buy recommendation on stocks that have 'best' characteristics. This finding is in line with the findings of, for example, Stickel (2000). The 'best' characteristics namely, positive price momentum, larger market capitalisation and lower book-to-market, are linked to higher future returns by the anomaly literature. Chan et al., (1996) find higher returns following positive price momentum. This might be the reason why analysts place so much importance on stocks' previous performance. Also, the empirical evidence (e.g., Fama and French, 1992, Lakonishok et al.,1994) shows that abnormal returns are earned by stocks with low book-to-market, suggesting that financial analysts should issue a buy rating on the stocks that have low book-to-market but as shown above they do just the opposite. Again, empirical evidence (e.g., Banz, 1981; Fama and French, 1992) shows that stocks with lower market capitalisation have higher returns. Here too, analysts do just the opposite by awarding a buy rating to stocks with large market capitalisation. It is possible that financial analysts issue buy rating to large market capitalisation stocks because, among other things, stocks with higher market capitalisation have the potential for greater investment banking. My findings and what has been documented in the finance literature so far are outstanding examples of analysts' representativeness bias when they make a decision on the type of rating to award to stocks.

Over the sample period, price momentum and book-to-market are the two measures of representativeness bias which differentiate between nonconforming buy and sell recommendations. Analysts' following comes out significantly as well, which is interpreted as showing that strong analyst following is essential in predicting nonconforming stock recommendations.

During the bull market when the stock prices are generally increasing and the economic conditions are flourishing. The only measure of representativeness bias that analysts

rely upon to make their decisions on the type of rating is momentum. But during the bear market when the stock prices are decreasing and the economic conditions are somehow gloomy for investing, analysts tend to rely on other measures of representativeness bias as well (i.e., size of the firm and book-to-market) in addition to momentum. Reliance on additional measures of psychological bias during the bear market is not surprising given the bear market conditions.

Momentum seems to be a consistently important psychological factor both before and after NASD 2711, but what is interesting is the fact that after NASD 2711, its significance is reduced substantially. The significance of firm size is also not at the maximum at this time. These results are interpreted as showing that the requirements of NASD 2711, which include the fact that analysts should display the proportion of issuing firm's recommendations that are buys, holds and sells, have helped to reduce but not obliterate analysts' representativeness bias, particularly the representativeness bias as measured by reliance on momentum.

While other factors such as firm size and book-to-market are important in their own right in differentiating nonconforming stock recommendations, it is interesting that price momentum is the only persistent factor in differentiating between nonconforming buys and sells in the whole sample period, during the bull and the bear markets and before and after the implementation of NASD 2711. The persistence of momentum shows that analysts believe that past winners are future winners while past losers are the losers of the next period (Jegadeesh and Titman, 1993, 2001). The findings in this study indicate that the momentum strategy does not work all the time, but analysts do not realise or adjust accordingly when this happens, but continue to issue stock recommendations that lack market impact. These results further show that analysts' representativeness bias, as measured by momentum, is at play almost all the time when analysts are making decisions about stock recommendations.

In summary, this chapter shows that the new buy stocks which lack market impact have characteristics that are preferred by financial analysts. The most important of these characteristics is positive price momentum which influences financial analysts

throughout the sample period and in different sub-periods. Thus, financial analysts use momentum strategy extensively when making decisions on what they perceive as an appropriate stock rating and do not take into account that momentum, like any other strategy, does not always work. The fact that the stock recommendations do not perform as expected, particularly buy recommendations, may be interpreted as showing that investors do realise when analysts are psychologically biased by relying too heavily on factors such as momentum or size of the firm to make recommendation decisions and as a result are (investors) able to discount analysts' bias accordingly. If this interpretation is correct, I may as well argue that investors may not have been misled to a great extent in the last decade as alleged by the Global Settlement.

It is also interesting to observe the important role played by measures of representativeness bias in predicting nonconforming analysts' stock recommendations even without the variable that measures the corporate relationship between investment banks and firms. This result suggests the possibility that the rules and regulations that are meant to address the bias in analysts recommendations arising from corporate relationships are likely to have a limited role in addressing analysts' bias at large, as psychological bias, in particular representativeness, seems to be pervasive as well.

The next chapter summarises and makes conclusions about the findings in my thesis, present my contribution to theory and practice, points out the limitations and suggests opportunities for future research.

Chapter 10   Summary and conclusion, implications for theory and practice
limitations and future work

10.1 Introduction

This thesis sets out to investigate the following overarching research question, what are the factors associated with nonconforming new buy (sell) stock recommendations? In order to answer this question, two sets of literature which provide an overview of the job financial analysts do are reviewed. The two strands of literature are the traditional finance literature on the role of financial analysts in the stock market and the behavioural finance literature which provides information about the cognitive thinking of analysts. To answer my basic research question I develop hypotheses in chapter 3 and explain the methodologies I employ to answer the research questions and test my hypotheses in chapter 4. I conduct a pilot study to test whether the content analysis method I employ works. The procedure, data and results of my pilot study are presented in chapter 5. Chapter 6 provides my data selection process, details of the data and a description of the stock recommendation and target price characteristics of my sample data.

The aim of my empirical work is to establish why some stocks which receive new buy or new sell recommendations do not necessarily perform as expected in the subsequent 12 months. I evaluate stock recommendation and target price performance as well as select conforming and nonconforming stock recommendations in chapter 7. The performance of target prices is also evaluated because analysts often issue target prices concurrent with stock recommendations, which implies stock recommendations may be drivers of target prices and they are both important financial analysts' outputs.

Chapter 8 tests for the psychological factors that are associated with nonconforming stock recommendations using logistic regression analysis. In this analysis, RATING is a dependent variable which takes the value 1 if a stock receives a new buy recommendation and underperforms the benchmark by $<-20\%$ or more over the subsequent 12 month period and 0 if the stock receives a sell recommendation and outperforms the benchmark by $>+20\%$ or more. The dependent variables are as depicted by my conceptual model in section 2.4 with the exception of corporate information.

Chapter 9 takes the analysis in chapter 8 further by investigating representativeness bias in nonconforming stock recommendations during the sample period, during the bull and the bear markets, and before and after the implementation of NASD 2711. The sample size used for the analysis in this chapter is larger than the sample size in chapter 8 as there are no sample size restrictions imposed by research report characteristics. The main aim of this chapter is to specifically assess the role of analysts' representativeness bias in issuing nonconforming stock recommendations. As in chapter 8, in this analysis, underperforming new buys are those that underperform the respective benchmark by $<-20\%$ while sells are those that outperform the benchmark by $>+20\%$. To establish which representativeness bias factors underlie these nonconforming stocks, I fit the logistic regression model where RATING is a dependent variable which takes a value of 1 if the stock is underperforming new buy and 0 otherwise. The independent variables are momentum, size, and book-to-market while analyst following is a control variable.

In this final chapter, a summary and discussion of my main empirical findings are first provided in section 10.2. This is followed by a discussion of the implications of my results for theory in section 10.3. Section 10.4 discusses my results' implications for public policy and practice. Section 10.5 discusses the limitations of this research and the final section outlines possible future developments.

10.2 Summary and Discussion

Research shows that until very recently, analysts' stock recommendations were very optimistic, i.e., analysts issued more buy recommendations than sells. Other studies point out that analysts' stock recommendations lack market impact, implying that investors would not profit from trading on analyst stock recommendations. In addition, another set of studies has alluded to the fact that the information analysts use in preparing their recommendations differs from that used to justify their recommendations. However, what is not clear in all these studies is what factors are actually influencing financial analysts to issue optimistic stock recommendations which do not seem to perform as expected. Also, where do analysts obtain the information that they use to make decisions on the stock recommendations if the information they use is

not from individual companies' financial reports? My initial proposition is that analysts' stock recommendations lack market impact because in making decisions about the type of rating to award stocks analysts are influenced by their psychological biases (in particular, overconfidence and representativeness) and are also influenced by the relationship between their investment bank employers and the firms they research.

To test my hypotheses about psychological bias and investment relationships in analysts' nonconforming stock recommendations, the first step is to evaluate the performance of stocks 12 months after the recommendations are changed from their previous categories to new buy and new sell categories. The intention is to select stocks that perform contrary to expectations after a change is made and analyse them further.

Chapter 7 shows the performance of stocks after they have been moved to new buy and new sell categories. The results show that in aggregate, analysts' stock recommendations do have an economic value. Thus, stocks that receive a new buy rating have an increased abnormal return. However, this abnormal return is only significant in month 0 which corroborates the findings of Stickel (1995), Womack (1996), Barber et al., (2001) and Ryan and Taffler (2005) that the value of new buy recommendations lasts only for one month. On the other hand, there is a continuing negative market reaction for up to 12 months after recommendations are changed to sell category. Again these findings support the findings of Stickel (1995), Womack (1996), Barber et al., (2001) and Ryan and Taffler (2005) that the market reaction to new sells lasts longer and is incomplete.

Similarly, there is a significant market reaction observed when target prices are changed. Increase in target prices results in stock price increases of 6.30% only in the month, suggesting that profit from trading on increased target prices last only for one month as is the case with new buys. The decrease in target price stocks accrues a negative abnormal return that lasts for up to 12 months after the change is made. Generally, the findings about target prices support the finding of Brav and Lehavy (2003) that target prices are informative.

Although the findings show that, in aggregate, new buy and new sell recommendations have economic value, most of the new buy recommendations actually underperform the benchmark while a relatively small percentage of new sells outperform the respective benchmarks in the subsequent 12 months after the change is made. Specifically, 55% of new buy recommendations earn negative abnormal returns over the 12 months period and 34% of those that underperform actually underperform the benchmark by -20% or more. On the other hand, 30% of new sell recommendations earn positive returns 12 months after the recommendations are changed to sell, but only 16% of these new sell stocks outperform the benchmark by +20% or more. From these findings I conclude that more than 50% of new buys do not accrue the expected return during the 12 months period after the change in recommendation is made, contrary to the prediction of financial analysts at the time that they issue a buy rating (see Appendix 1). Compared to new buys, a larger percentage of stocks that are awarded sell rating perform as expected, i.e., underperform the respective benchmark. Thus, about 84% of the new sell stocks earn negative abnormal returns over the period predicted by financial analysts. This finding about sells implies that new sell recommendations are more informative than new buys. The next interesting question, which is also the research question for this study, is what influences financial analysts to issue these recommendations that do not perform as expected or that lack market impact?

Chapter 8 shows that, as postulated by the conceptual model illustrated by figure 2-1 in section 2.4, there are certain factors that influence analysts to issue stock recommendations which lack market impact. My hypothesis is that analysts' decisions to issue nonconforming stock recommendations are associated with their psychological bias, in particular overconfidence (as measured by optimism and certainty in the tone language that analysts use to justify their recommendations) and representativeness (as measured by activity, momentum, size, book-to-market and target price) as well as the investment banking relationships that exist between investment banks and firms.

The logit analysis in section 8.3 shows that the probability that analysts will issue a buy recommendation that lacks market impact increases with analysts' optimism (a proxy for overconfidence bias). In addition to optimism, measures of representativeness bias,

positive previous stock price performance, market capitalisation, book-to-market and changes in target price are individually statistically significant in explaining analysts' nonconforming stock recommendations. Not surprisingly, a variable measuring the existence of the relationship between brokerage firm and a company is also significant.

Optimism serves as a proxy for analysts' overconfidence and is a measure of "language endorsing some person, group, concept or highlighting their positive entailment" (Hart, 2001 p. 45). Optimism is measured from the tone of language that analysts use in their research reports to justify the type of recommendations that they issue. Overconfidence is defined as overestimating what one can do compared to what circumstances would warrant. The findings, that overconfidence increases the chance of analysts issuing new buy recommendations that lack market impact, compel me to reject the null hypotheses that   the tone of language used by investment analysts in their research reports to justify the stock ratings is not optimistic and conclude that overconfidence bias is one of the factors that make analysts issue recommendations that lack market impact. These results are interpreted as showing that analysts believe they have superior investment abilities and tend to overestimate the likely performance of the stocks they follow. This argument is consistent with other studies such as Odean (1998 a and b); Barber and Odean (2001), and Massey and Thaler (2005) who document that when investors are faced with difficult tasks they tend to overestimate the precision of their information and thereby become overconfident. However, the difference between the current study and these studies lies in the methodology used to measure overconfidence. Thus, they assess overconfidence from the market reaction to the decisions made by analysts but fail to trace directly the existence of judgemental bias in the way that analysts prepare their reports. The current study highlights the fact that financial analysts' overconfidence observed in the market actually originates from their research reports.

Activity is used as a proxy for analysts' representativeness bias. Activity is a measure of "movement, change, [and] the implementation of ideas and avoidance of inertia" (Hart 2001 p. 46). Representativeness bias is defined by Tversky (1974) as decisions based on stereotypes. Various studies such as those of Shefrin and Statman (1995) have indicated that investors are influenced by representativeness bias. The findings in this

study do not support evidence that analysts use stereotypes such as using their knowledge of eminent mergers and acquisitions or change in management to justify their recommendations. This finding is also contrary to Fogarty and Rogers (2005) who document that analysts make positive recommendations about stocks if they know of the company's broad range of future plans for change, including mergers and acquisitions. The reasons for inconsistency of my results and existing literature may be due to different measurement methods. Thus, some of the studies measure representativeness bias using hard market data (as opposed to textual data except Fogarty and Rogers, 2005) while in the current study, Activity, as a measure of representativeness bias is measured from the tone of the language and other variables that analysts use to justify their recommendations. Measuring representativeness bias from research reports assumes that analysts will declare the stereotypes they use to make their recommendation decision, but this may not be the case.

The lack of evidence to support representativeness bias (as measured by Activity) is also inconsistent with the findings in the pilot study. The pilot study results indicated that the high level of activity within the company is believed to mean good for the future stock performance and vice versa. In other words, activity is seen as representative of future performance. The difference between the pilot results and the main study results with regard to representativeness bias may be due to different sample sizes. The pilot study sample was quite small compared to the main study sample. But most importantly, the procedure used to conduct the pilot study is different from the procedure used in the main study.

In addition to overconfidence, stocks' characteristics which serve as measures of representativeness bias are found to be important in influencing analysts' decisions on the type of stock rating to issue. Specifically, analysts prefer stocks with positive previous stock price performance and stocks with large market capitalisation and with high book-to-market. These results suggest that stock characteristics are very important for analysts' decision making regarding the future performance of the stocks. The findings echo the conclusion of Stickel (2000) and Jegadeesh et al., (2004) that analysts prefer stocks with 'best' characteristics.

The dependence on the previous price performance of stocks by analysts may be influenced by the findings of Jegadeesh and Titman (1993) that stocks that have performed well in the past will continue to perform well in the future. But, the fact that they also prefer large market capitalisation stocks is surprising because research (e.g., Fama and French, 1992) has established that smaller market capitalisation stocks have higher returns, in which case I would expect analysts to prefer stocks with smaller market capitalisation. The clear preference of stocks with positive characteristics may also be linked to representativeness bias documented by Solt and Statman (1989), Shefrin and Statman (1995), and DeBondt and Thaler (1985). They argue that analysts believe that past good performance represents good future performance and large market capitalisation represents good future performance.

The effect of size and book-to-market on stock returns is well documented in the literature. For instance Fama and French (1992) find that book-to-market, together with firm size, has a significant relation with future stock returns. It is interesting therefore, to find that these two factors (which measure representativeness bias in this study) underlie analysts' recommendations that lack market impact as well.

Not surprisingly, the change in target price influences the type of recommendation that analysts issue. Thus, the probability of obtaining a buy recommendation that underperforms the benchmark increases with an increase in target price. Although Brav and Lehavy (2003) conclude that target prices are informative when used with or without stock recommendations, from the findings in this study it is not very clear what the role of target price is. It could be argued that the target prices that are issued concurrent with stock recommendations serve only as a way for analysts to ameliorate the effects of their overly optimistic or overly pessimistic reports, or as part of the sales hype to peddle stocks (Asquith et al., 2005).

Interestingly, conflicts of interest are also found to have a significant impact on the type of recommendations that analysts issue. These findings are consistent with the findings of Lin and McNichols (1998) and other studies (e.g., Barber et al., 2004; Cliff, 2004,

Agrawal and Chen, 2005; and Madureira, 2004) that have been carried out after the implementation of various rules that are meant to govern analysts. All these studies conclude that the relationships between brokerage firms and companies have an effect on analysts' decisions about stock ratings. The results further confirm the recent concern by policy-makers and investors that analysts' recommendations do not reflect their true beliefs about the stocks they follow. Further, the findings justify the regulations that have been implemented recently by policy-makers to govern analysts and brokerage firms.

Chapter 9 serves as a further test of my basic thesis that analysts' decisions to issue nonconforming stock recommendations are driven by their psychological biases, in this case representativeness bias is measured by momentum, size and book-to-market. Over the sample period, price momentum and book-to-market are the two measures of representativeness bias which differentiate between nonconforming buy and sell recommendations. During the bull market the only measure of representativeness bias that analysts appear to rely upon to make their decisions on the type of rating is momentum. But during the bear market when stock prices are decreasing and the economic conditions are gloomy for investing, analysts tend to rely on other measures of representativeness bias as well (i.e., they also rely on size of the firm and book-to-market) in addition to momentum. Reliance on additional measures of psychological bias during the bear market is not surprising given the bear market conditions.

Momentum seems to be the consistently important psychological factor both before and after NASD 2711, but what is interesting is the fact that after NASD 2711, its significance is reduced substantially. These results are interpreted as showing that the requirements of NASD 2711, which include the fact that analysts should display the proportion of issuing firm's recommendations that are buys, holds and sells, have helped to reduce but not obliterate analysts' representativeness bias, particularly the representativeness bias as measured by reliance on momentum. This result implies that analysts have to think more deeply about why they are making particular recommendations.

While other factors such as firm size and book-to-market are important in their own right in differentiating between nonconforming stock recommendations, it is interesting that price momentum is the only persistent factor in differentiating between nonconforming buys and sells in the whole sample period, during the bull and the bear markets and before and after the implementation of NASD 2711. The persistence of momentum shows that analysts believe that past winners are future winners while past losers are the losers of the next period (Jegadeesh and Titman, 1993, 2001). The findings in this study indicate that the momentum strategy does not work all the time, but analysts do not realise or adjust accordingly when this happens, but continue to issue stock recommendations that lack market impact. These results further show that analysts' representativeness bias as measured by momentum is at play almost all the time when analysts are making decisions about stock recommendations

The research question addressed in this study is to establish the factors that are associated with optimistic analysts' recommendations which lack market impact, particularly the role of overconfidence and representativeness bias. From my analysis, I conclude that overconfidence bias (as measured by optimism), representativeness bias (as measured by price momentum, firm price, book-to-market, compensation, target price) and corporate finance relationships between investment banks and firms are the main factors that are associated with analysts' nonconforming stock recommendations. Therefore, the conceptual framework in figure 2-1, section 2.4 needs to be modified to reflect only those factors that are supported by the empirical evidence.

This research contributes to research on the current furore about whether analysts' optimistic recommendations are influenced by analysts' conflicts of interest and also of whether implementation of regulations to govern analysts will be efficient in the long-term. Unlike most studies in this area, this study specifically analyses stocks that lack market impact. Investigating stocks that lack market impact alone provides a clean test of the factors that could have influenced analysts to issue these stocks in the first place.

The rules implemented to date in the US address the optimism in analysts' recommendations arising from the relationships that investment banks (conflicts of

interest) have with firms, suggesting that SEC and agencies believe that the problem of optimistic recommendations is a problem caused by conflict of interest only. The current study looks at the problem of optimistic recommendations from a broader perspective and shows that there are other factors over and above conflicts of interest that are causing the problem, in particular, analyst cognitive bias.

10.3 Implications for theory

Research has established that financial analysts' stock recommendations have substantial market impact (e.g., Womack, 1996 and Ryan and Taffler, 2005). The results of this study confirm the findings in these earlier studies that, in aggregate, there is a significant market reaction to changes in recommendations. However, the current studies contribute further by showing that when performance is disaggregated, there is a large proportion of buy and new sell recommendations that does not perform as predicted by analysts. However, the problem of lack of market impact is more prevalent with new buy recommendations than with new sells.

Other studies have shown, however, that after taking into account the transaction costs, investors do not profit from trading on analysts stock recommendations (e.g. Barber et al., 2001; Mikhail et al., 2004). Theoretically, it is expected that analysts' recommendations would have significant impact, given that they have both public and private information about the stocks they follow. These studies, however, do not go any further to investigate why analysts are issuing the recommendations that lack market impact in the first place. This research augments these studies by identifying the factors that influence analysts to issue stock recommendations that lack market impact by using a theoretically derived and empirically tested framework. The empirical framework developed is robust as it also provides an answer to the issues raised in other studies such as Rogers and Grant (1997), Breton and Taffler (2001) and Amir et al., (1999) that the information which analysts actually use differs from that used to justify their recommendations.

It has been highlighted in chapter 4 that measuring analysts' cognitive biases outside the abstracted situation of a psychological laboratory is very difficult. This may be a reason

why various studies that document the psychological biases to which analysts might be prone, only look into how stocks might react to their recommendations (see Barberis et al., 1998, Daniel et al., 1998 and DeBondt and Thaler, 1985) but fail to trace directly the existence of judgemental bias in the way that analysts prepare their reports. This research contributes methodologically by tracing the existence of heuristics from the financial markets back to the way that analysts prepare their reports. Thus, the documented cognitive biases, particularly overconfidence can be measured by the tone of language that analysts use in their reports.

10.4 *Implications for policy and practice*

The issue of analysts' optimistic recommendations is currently of significant concern to the SEC and other agencies such as the NASD and NYSE. This research makes a contribution to their public policy task. In the recent past the SEC, NYSE, NASD and the New York Attorney General have issued rules and regulations (i.e. Regulation Fair Disclosure, NASD 2711, Rule 472 and Global Analyst Research Settlement) to govern analysts and brokerage firms. Effectively all these bodies assumed the problem of optimistic research recommendations to be caused by analysts' conflicts of interest that arise from the firms' corporate relationships with investment banks. However, this research shows that in addition to their conflicts of interest, other factors such as psychological biases (overconfidence and representativeness) influence the type of recommendations that analysts issue. These findings imply that the regulations that are set up to govern analysts may work only in as far as regulating their conflicts of interest but cannot regulate other factors, such as psychological biases which are found to play a significant role in this research. Studies on conflicts of interest such as Kadan et al., (2004) and Kolasinski and Kothari (2004) conclude that conflicts of interest do not explain all the bias in analysts' recommendations. Although they posit that the remaining bias is due to selection bias, it is argued here that the remaining bias is also due to analysts' overconfidence and representativeness bias.

This research should also be of importance to both investors and analysts. Once investors (including naïve investors) are aware of the factors that influence analysts in addition to conflicts of interest, they may be able to filter analyst recommendations

accordingly before acting on them. On the other hand, this study may help analysts to review their role in the financial markets to facilitate regaining a complete investor confidence through debiasing themselves.

10.5 Limitations

The findings in this study are subject to the following limitations:

a) The main analysis in this research is on the factors driving analysts' recommendations that are found to lack necessary market impact. As such the inferences drawn on the findings are limited to this set of stocks only and not to the stocks that have market impact.

b) The factors that influence analysts' stock recommendations as depicted by the conceptual model are developed from theory. However, these factors have been selected idiosyncratically. It is possible that there are other factors that may explain analysts' recommendations which are not included in the model used. The inclusion of additional factors or exclusion of some of the currently included factors in the model may change the inferences made.

c) An effort was made to use the most appropriate return-generating model to evaluate the performance of stock with changes in recommendations. However, it is likely that the use of a different return generating model will produce different results.

10.6 Implications for further work

The current research brings together traditional finance and behavioural finance and has crucial public policy implications by shedding light on the factors that influence financial analysts to issue stock recommendations that lack necessary market impact. Any further work in these areas, which builds on the results of this study has a potential to contribute to further knowledge.

The main idea in this research is to investigate the role of psychological biases (overconfidence and representativeness) in influencing analysts to issue a particular recommendation on a stock. Investigating financial analysts' cognitive thinking in laboratory experiments may provide more robust results in the role of psychological biases on influencing analysts' stock recommendations. In addition, other research methodologies such as questionnaires may be used to gather information from analysts regarding what they perceive to be the main factors influencing their decisions. Obtaining data directly from analysts by way of experiment or questionnaire may provide more authentic results about the factors that affect their decision-making about stock recommendations than methodologies that make inferences about analysts' behaviour from publicly available data.

There has been extensive research on analysts' conflicts of interest particularly after the implementation of recent rules that govern analysts and brokerage houses. Overall, these studies investigate optimism in stock recommendations of affiliated and unaffiliated brokerage firms. Future work may take these studies further by investigating the extent to which all the significant factors found in this study differentiate between affiliated and unaffiliated brokerage houses.

The latest in the regulations implemented is the Global Settlement. It would, therefore, be interesting in further work to establish whether conflict of interest is still significant.

Finally, for this study to have a broader impact, it could be replicated in other environments, such as the UK, to explore the impact of different institutional contexts. The results from such a study could provide a broader understanding of analyst behaviour across different international markets, places of value to international investors and international regulators.

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Appendices

Appendix 1: Brokerage firms' definition of stock recommendations

1) **Credit Suisse First Boston**
Analysts' stock ratings are defined as follows:

Outperform: The stock's total return is expected to exceed the industry average* by at least 10-15%(or more, depending on perceived risk) over the next 12 months.

Neutral: The stock's total return is expected to be in line with the industry average*(range of (10%) over the next 12 months.

Underperform**: The stock's total return is expected to underperform the industry average* by 10-15% or more over the next 12 months.

*The industry average refers to the average total return of the analyst's industry coverage universe(except with respect to Asia/Pacific, Latin America and Emerging Markets, where stock ratings are relative to the relevant country index, and CSFB HOLT Small and Mid-Cap Advisor stocks, where stock ratings are relative to the regional CSFB HOLT Small and Mid-Cap Advisor investment universe.

**In an effort to achieve a more balanced distribution of stock ratings, the Firm has requested that analysts maintain at least 15% of their rated coverage universe as Underperform. This guideline is subject to change depending on several factors, including general market conditions.

Restricted: In certain circumstances, CSFB policy and/or applicable law and regulations preclude certain types of communications, including an investment recommendation, during the course of CSFB's engagement in an investment banking transaction and in certain other circumstances.

Volatility Indicator (V): A stock is defined as volatile if the stock price has moved up or down by 20% or more in a month in at least 8 of the past 24 months or the analyst expects significant volatility going forward. All CSFB HOLT Small and Mid-Cap Advisor stocks are automatically rated volatile. All IPO stocks are automatically rated volatile within the first 12 months of trading.

Analysts' coverage universe weightings are defined as follows*:

Overweight: Industry expected to outperform the relevant broad market benchmark over the next 12 months.

Market Weight: Industry expected to perform in-line with the relevant broad market benchmark over the next 12 months.

Underweight: Industry expected to underperform the relevant broad market benchmark over the next 12 months.

*CSFB HOLT Small and Mid-Cap Advisor stocks do not have coverage universe weightings.

2) <u>UBS Warburg</u>

UBS Investment Research Global Ratings: Definitions and Allocations

UBS rating	Definition	UBS rating	Definition	Rating category	Coverage[1]	IB services[2]
Buy 1	FSR is > 10% above the MRA, higher degree of predictability	Buy 2	FSR is > 10% above the MRA, lower degree of predictability	Buy	41%	36%
Neutral 1	FSR is between -10% and 10% of the MRA, higher degree of predictability	Neutral 2	FSR is between -10% and 10% of the MRA, lower degree of predictability	Hold/Neutral	50%	31%
Reduce 1	FSR is > 10% below the MRA, higher degree of predictability	Reduce 2	FSR is > 10% below the MRA, lower degree of predictability	Sell	9%	31%

1: Percentage of companies under coverage globally within this rating category.
2: Percentage of companies within this rating category for which investment banking (IB) services were provided within the past 12 months.

Source: UBS; as of 31 March 2004.

KEY DEFINITIONS
Forecast Stock Return (FSR) is defined as expected percentage price appreciation plus gross dividend yield over the next 12 months.

Market Return Assumption (MRA) is defined as the one-year local market interest rate plus 5% (an approximation of the equity risk premium).

Predictability Level The predictability level indicates an analyst's conviction in the FSR. A predictability level of '1' means that the analyst's estimate of FSR is in the middle of a narrower, or smaller, range of possibilities. A predictability level of '2' means that the analyst's estimate of FSR is in the middle of a broader, or larger, range of possibilities.

Under Review (UR) Stocks may be flagged as UR by the analyst, indicating that the stock's price target and/or rating are subject to possible change in the near term, usually in response to an event that may affect the investment case or valuation.

Rating/Return Divergence (RRD) This qualifier is automatically appended to the rating when stock price movement has caused the prevailing rating to differ from that which would be assigned according to the rating system and will be removed when there is no longer a divergence, either through market movement or analyst intervention.

3) <u>Prudential</u>
When we assign an Overweight rating, we mean that we expect that the stock's total return will exceed the average total return of all of the stocks covered by the analyst (or analyst team). Our investment time frame is 12-18 months except as otherwise specified by the analyst in the report.
When we assign a Neutral Weight rating, we mean that we expect that the stock's total return will be in line with the average total return of all of the stocks covered by the

analyst (or analyst team). Our investment time frame is 12-18 months except as otherwise specified by the analyst in the report.

When we assign an Underweight rating, we mean that we expect that the stock's total return will be below the average total return of all of the stocks covered by the analyst (or analyst team). Our investment time frame is 12-18 months except as otherwise specified by the analyst in the report.

4) **Lehman Brothers**
Stock Rating

1-Overweight - The stock is expected to outperform the unweighted expected total return of the industry sector over a 12-month investment horizon.

2-Equal weight - The stock is expected to perform in line with the unweighted expected total return of the industry sector over a 12-month investment horizon.

3-Underweight - The stock is expected to underperform the unweighted expected total return of the industry sector over a 12-month investment horizon.

RS-Rating Suspended - The rating and target price have been suspended temporarily to comply with applicable regulations and/or firm policies in certain circumstances including when Lehman Brothers is acting in an advisory capacity on a merger or strategic transaction involving the company.

Sector View
1-Positive - sector fundamentals/valuations are improving.
2-Neutral - sector fundamentals/valuations are steady, neither improving nor deteriorating.
3-Negative - sector fundamentals/valuations are deteriorating.

Stock Ratings From February 2001 to August 5, 2002 (sector view did not exist): This is a guide to expected total return (price performance plus dividend) relative to the total return of the stock's local market over the next 12months.
1-Strong Buy - expected to outperform the market by 15 or more percentage points.
2-Buy - expected to outperform the market by 5-15 percentage points.
3-Market Perform - expected to perform in line with the market, plus or minus 5 percentage points.
4-Market underperform - expected to underperform the market by 5-15 percentage points.
5-Sell - expected to underperform the market by 15 or more percentage points.

5) **Salomon Smith Barney**
Guide To Investment Ratings:
Smith Barney's stock recommendations include a risk rating and an investment rating.
Risk ratings, which take into account both price volatility and fundamental criteria, are: Low (L), Medium (M), High (H), and Speculative (S). Investment ratings are a function of Smith Barney's expectation of total return (forecast price appreciation and dividend yield within the next 12 months) and risk rating.

For securities in developed markets (US, UK, Europe, Japan, and Australia/New Zealand), investment ratings are: Buy (1) (expected total return of 10% or more for Low-Risk stocks, 15% or more for Medium-Risk stocks, 20% or more for High-Risk stocks, and 35% or more for Speculative stocks); Hold (2) (0%-10% for Low-Risk stocks, 0%-15% for Medium-Risk stocks, 0%-20% for High-Risk stocks, and 0%-35% for Speculative stocks); and Sell (3) (negative total return). Investment ratings are determined by the ranges described above at the time of initiation of coverage, a change in risk rating, or a change in target price. At other times, the expected total returns may fall outside of these ranges because of price movement and/or volatility. Such interim deviations from specified ranges will be permitted but will become subject to review by Research Management. Your decision to buy or sell a security should be based upon your personal investment objectives and should be made only after evaluating the stock's expected performance and risk.

Between September 9, 2002, and September 12, 2003, Smith Barney's stock ratings were based upon expected performance over the following 12 to 18 months relative to the analyst's industry coverage universe at such time. An Outperform (1) rating indicated that we expected the stock to outperform the analyst's industry coverage universe over the coming 12-18 months. An In-line (2) rating indicated that we expected the stock to perform approximately in line with the analyst's coverage universe. An Underperform (3) rating indicated that we expected the stock to underperform the analyst's coverage universe. In emerging markets, the same ratings classifications were used, but the stocks were rated based upon expected performance relative to the primary market index in the region or country. Our complementary Risk rating system -- Low (L), Medium (M), High (H), and Speculative (S) -- took into account predictability of financial results and stock price volatility. Risk ratings for Asia Pacific were determined by a quantitative screen which classified stocks into the same four risk categories. In the major markets, our Industry rating system -- Overweight, Marketweight, and Underweight -- took into account each analyst's evaluation of their industry coverage as compared to the primary market index in their region over the following 12 to 18 months.

Prior to September 9, 2002, the Firm's stock rating system was based upon the expected total return over the next 12 to 18 months. The total return required for a given rating depended on the degree of risk in a stock (the higher the risk, the higher the required return). A Buy (1) rating indicated an expected total return ranging from +15% or greater for a Low-Risk stock to +30% or greater for a Speculative stock. An Outperform (2) rating indicated an expected total return ranging from +5% to +15% (Low-Risk) to +10% to +30% (Speculative). A Neutral (3) rating indicated an expected total return ranging from -5% to +5% (Low-Risk) to -10% to +10% (Speculative). An Underperform (4) rating indicated an expected total return ranging from -5% to -15% (Low-Risk) to -10% to -20% (Speculative). A Sell (5) rating indicated an expected total return ranging from
-15% or worse (Low-Risk) to -20% or worse (Speculative). The Risk ratings were the same as in the current system.

6) <u>Morgan Stanley</u>

Analyst Stock Ratings

Overweight (O). The stock's total return is expected to exceed the average total return of the analyst's industry (or industry team's) coverage universe, on a risk-adjusted basis, over the next 12-18 months.

Equal-weight (E). The stock's total return is expected to be in line with the average total return of the analyst's industry (or industry team's) coverage universe, on a risk-adjusted basis, over the next 12-18 months.

Underweight (U). The stock's total return is expected to be below the average total return of the analyst's industry (or industry team's) coverage universe, on a risk-adjusted basis, over the next 12-18 months.

More volatile (V). We estimate that this stock has more than a 25% chance of a price move (up or down) of more than 25% in a month, based on a quantitative assessment of historical data, or in the analyst's view, it is likely to become materially more volatile over the next 1-12 months compared with the past three years. Stocks with less than one year of trading history are automatically rated as more volatile (unless otherwise noted). We note that securities that we do not currently consider "more volatile" can still perform in that manner.

Unless otherwise specified, the time frame for price targets included in this report is 12 to 18 months. Ratings prior to March 18, 2002: SB = Strong Buy; OP = Outperform; N = Neutral; UP = Underperform. For definitions, please go to http://www.morganstanley.com/companycharts

Analyst Industry Views

Attractive (A). The analyst expects the performance of his or her industry coverage universe over the next 12-18 months to be attractive vs. the relevant broad market benchmark named on the cover of this report.

In-Line (I). The analyst expects the performance of his or her industry coverage universe over the next 12-18 months to be in line with the relevant broad market benchmark named on the cover of this report.

Cautious (C). The analyst views the performance of his or her industry coverage universe over the next 12-18 months with caution vs. the relevant broad market benchmark named on the cover of this report.

7) <u>Bear, Stearns & Co. Equity Research Rating System</u>:

Ratings for Stocks (vs. analyst coverage universe):

Outperform (O) - Stock is projected to outperform analyst's industry coverage universe over the next 12 months.

Peer Perform (P) - Stock is projected to perform approximately in line with analyst's industry coverage universe over the next 12 months.

Underperform (U) - Stock is projected to underperform analyst's industry coverage universe over the next 12 months.

Ratings for Sectors (vs. regional broader market index):
Market Overweight (MO) - Expect the industry to perform better than the primary market index for the region over the next 12 months.

Market Weight (MW) - Expect the industry to perform approximately in line with the primary market index for the region over the next 12 months.

Market Underweight (MU) - Expect the industry to underperform the primary market index for the region over the next 12 months.

8) Merrill Lynch
Opinon Key:

Opinon include a volatility Risk Rating, Intermediate-Term and Long-term Investment ratings and Income Ratings.
VOLATILITY RISK RATINGS – indicators of potential price fluctuations. Are A – low, B – Average, D-high.
INTERMEDIATE-TERM INVESTMENT RATINGS, indicators of expected total return (price appreciation plus yield) within the 12 months period from the date of initial rating are:
Strong Buy (minimum 20%...more for high risk securities
Buy (minimum 10%)
Neutral (0-10%)
Reduce/sell (negative return)
No rating
LONG-TERM INVESTMENT RATINGS, indicators of fundamental company factors demonstrating potential total return for the 3-year period from the period of the initial rating, are
Strong Buy (aggregate minimum 40%)
Buy (aggregate minimum 20%)
Neutral (aggregate 0-20%)
Reduce/Sell (negative return
No Rating
INCOME RATINGS
Indicators of potential cash dividends are:
Same/higher (dividends considered to be secure)
Same/lower (dividends not considered to be secure)
Pays no dividends

9) Deutsche Bank: Definition not found

10) Goldman Sachs: Definitions not found

Appendix 2: Formulas for Diction's variables used and description of dictionaries and scores

Formulas for the Master Variables

Certainty = [Tenac. + Level. + Collec. + Insist.] - [Numer. + Ambiv. + Self + Variety]

Optimism = [Praise + Satis. + Inspir.] - [Blame + Hard. +Denial]

Activity = [Aggres. + Accomp. + Commun. + Motion] - [Cog. + Passv. + Embell.]

Calculated variables

Insistence, a measure of "code-restriction" that indicates a "preference for a limited, ordered world"

embellishment, a measure of the ratio of adjectives to verbs; (3) **variety**, a measure of conformity to, or avoidance of, a limited set of expressions (different words/total words)

variety, a measure of conformity to, or avoidance of, a limited set of expressions (different words/total words);

Description of the dictionaries and scores

Praise: Affirmations of some person, group, or abstract entity. Included are terms isolating important social qualities (dear, delightful, witty), physical qualities (mighty, handsome, beautiful), intellectual qualities (shrewd, bright, vigilant, reasonable), entrepreneurial qualities (successful, conscientious, renowned), and moral qualities (faithful, good, noble). All terms in this dictionary are adjectives.

Satisfaction: Terms associated with positive affective states (cheerful, passionate, happiness), with moments of undiminished joy (thanks, smile, welcome) and pleasurable diversion (excited, fun, lucky), or with moments of triumph (celebrating, pride, auspicious). Also included are words of nurturance: healing, encourage, secure, relieved.

Inspiration: Abstract virtues deserving of universal respect. Most of the terms in this dictionary are nouns isolating desirable moral qualities (faith, honesty, self-sacrifice, virtue) as well as attractive personal qualities (courage, dedication, wisdom, mercy). Social and political ideals are also included: patriotism, success, education, justice.

Blame: Terms designating social inappropriateness (mean, naive, sloppy, stupid) as well as downright evil (fascist, blood-thirsty, repugnant, malicious) compose this dictionary. In addition, adjectives describing unfortunate circumstances (bankrupt, rash, morbid, embarrassing) or unplanned vicissitudes (weary, nervous, painful, detrimental) are included. The dictionary also contains outright denigrations: cruel, illegitimate, offensive, miserly.

Hardship: This dictionary contains natural disasters (earthquake, starvation, tornado, pollution), hostile actions (killers, bankruptcy, enemies, vices) and censurable human behavior (infidelity, despots, betrayal). It also includes unsavory political outcomes (injustice, slavery, exploitation, rebellion) as well as normal human fears (grief, unemployment, died, apprehension) and incapacities (error, cop-outs, weakness).

Denial: A dictionary consisting of standard negative contractions (aren't, shouldn't, don't), negative functions words (nor, not, nay), and terms designating null sets (nothing, nobody, none).

Aggression: A dictionary embracing human competition and forceful action. Its terms connote physical energy (blast, crash, explode, collide), social domination (conquest, attacking, dictatorships, violation), and goal-directedness (crusade, commanded, challenging, overcome). In addition, words associated with personal triumph (mastered, rambunctious, pushy), excess human energy (prod, poke, pound, shove), disassembly (dismantle, demolish, overturn, veto) and resistance (prevent, reduce, defend, curbed) are included.

Accomplishment: Words expressing task-completion (establish, finish, influence, proceed) and organised human behavior (motivated, influence, leader, manage). Includes capitalistic terms (buy, produce, employees, sell), modes of expansion (grow, increase, generate, construction) and general functionality (handling, strengthen, succeed, outputs). Also included is programmatic language: agenda, enacted, working, leadership.

Communication: Terms referring to social interaction, both face-to-face (listen, interview, read, speak) and mediated (film, videotape, telephone, e-mail). The dictionary includes both modes of intercourse (translate, quote, scripts, broadcast) and moods of intercourse (chat, declare, flatter, demand). Other terms refer to social actors (reporter, spokesperson, advocates, preacher) and a variety of social purposes (hint, rebuke, respond, persuade).

Motion: Terms connoting human movement (bustle, job, lurch, leap), physical processes (circulate, momentum, revolve, twist), journeys (barnstorm, jaunt, wandering, travels), speed (lickety-split, nimble, zip, whistle-stop), and modes of transit (ride, fly, glide, swim).

Cognitive Terms: Words referring to cerebral processes, both functional and imaginative. Included are modes of discovery (learn, deliberate, consider, compare) and domains of study (biology, psychology, logic, economics). The dictionary includes mental challenges (question, forget, re-examine, paradoxes), institutional learning practices (graduation, teaching, classrooms), as well as three forms of intellection: intuitional (invent, perceive, speculate, interpret), rationalistic (estimate, examine, reasonable, strategies), and calculative (diagnose, analyse, software, fact-finding).

Passivity: Words ranging from neutrality to inactivity. Includes terms of compliance (allow, tame, appeasement), docility (submit, contented, sluggish), and cessation (arrested, capitulate, refrain, yielding). Also contains tokens of inertness (backward,

immobile, silence, inhibit) and disinterest (unconcerned, nonchalant, stoic), as well as tranquillity (quietly, sleepy, vacation).

Tenacity: All uses of the verb "to be" (is, am, will, shall), three definitive verb forms (has, must, do) and their variants, as well as all associated contractions (he'll, they've, ain't). These verbs connote confidence and totality.

Leveling: Words used to ignore individual differences and to build a sense of completeness and assurance. Included are totalizing terms (everybody, anyone, each, fully), adverbs of permanence (always, completely, inevitably, consistently), and resolute adjectives (unconditional, consummate, absolute, open-and-shut).

Collectives: Singular nouns connoting plurality that function to decrease specificity. These words reflect a dependence on categorical modes of thought. Included are social groupings (crowd, choir, team, humanity), task groups (army, congress, legislature, staff) and geographical entities (county, world, kingdom, republic).

Numerical Terms: Any sum, date, or product specifying the facts in a given case. This dictionary treats each isolated integer as a single "word" and each separate group of integers as a single word. In addition, the dictionary contains common numbers in lexical format (one, tenfold, hundred, zero) as well as terms indicating numerical operations (subtract, divide, multiply, percentage) and quantitative topics (digitize, tally, mathematics). The presumption is that Numerical Terms hyper-specify a claim, thus detracting from its universality.

Ambivalence: Words expressing hesitation or uncertainty, implying a speaker's inability or unwillingness to commit to the verbalization being made. Included are hedges (allegedly, perhaps, might), statements of inexactness (almost, approximate, vague, somewhere) and confusion (baffled, puzzling, hesitate). Also included are words of restrained possibility (could, would, he'd) and mystery (dilemma, guess, suppose, seems).

Self-Reference: All first-person references, including I, I'd, I'll, I'm, I've, me, mine, my, myself. Self-references are treated as acts of "indexing" whereby the locus of action appears to reside in the speaker and not in the world at large (thereby implicitly acknowledging the speaker's limited vision).

[source: http://rhetorica.net/diction.htm]