An investigation into momentum in the UK stock market and the behaviour of brokers and analysts

Áine Murphy
BBS, MBS

A dissertation submitted to Waterford Institute of Technology in fulfilment of Doctor of philosophy degree

Supervisors: Dr. Cormac O'Keeffe

Prof. William Forbes

Submitted to Waterford Institute of Technology March 2017

Declaration

The author hereby declares that, except where duly acknowledged, this thesis is her own work.

Áine Murphy

March 2017

Acknowledgements

Firstly I would like to express my gratitude to my supervisors Dr. Cormac O'Keeffe and Prof. William Forbes, for the continued support, patience, motivation and guidance to allow for the completion of this PhD.

Thanks also to Dr. Chen Su for his collaboration and research support.

To my colleagues and staff at the AIB Centre for Finance and Business Research for their ongoing support and advice over the course of this research, in particular to Dr. Sheila O'Donohoe for being an ever-present support throughout my time in WIT.

To my loving family and friends, thank you so much for your constant love and support, I hope you know how much each and every one of you mean to me. A very special mention for to the five little men in my life, for always bringing a smile to my face.

Table of Contents

Abstract

An investigation into momentum in the UK stock market and the behaviour of brokers and analysts

Áine Murphy

The efficiency of financial markets has been, and still is, a contentiously debated topic throughout the years. The momentum trading strategy has long since been recognised as a continuing anomaly in international markets, with rational explanations failing to explain the arbitrage possibilities as a result of engaging in a momentum trading strategy. Furthermore, the behaviour and impact of analyst output, particularly during times of economic crisis, is constantly being scrutinised.

To this end, this thesis aims to determine if abnormal returns can be generated in the presence of momentum in the UK stock market between 1995 and 2015. Furthermore, research on the presence of industry momentum in the UK market is lacking, this thesis aims to fill this research gap whilst adding to existing literature on the topic. Additionally, the role of analysts and the value and veracity of their recommendations in times of economic crisis is documented.

Momentum returns are generated in the UK stock market for both individual stock portfolios and industry portfolios, however, individual momentum is a better performing strategy overall. The performance of the momentum strategy appears to deteriorate in the latter years of this study. At the firm level analysts' advice appears to contain investment value at least during the Internet bubble years. However, at an aggregate level no stable relationship is found between stock returns and various measures of analysts' advice.

From an investment perspective the results imply that individual momentum strategies are more profitable in the UK market compared to industry momentum strategies. Analysts' advice at the aggregate level lacks predictive power; however, at the firm level investment value is apparent during the Internet bubble period.

List of abbreviations

AMEX	American Stock Exchange
BF	Behavioural Finance
BFI	Banking, Finance and Investments
BHAR	Buy and Hold Return
CAPM	Capital Asset Pricing Model
CAR	Cumulative Abnormal Returns
CRR	Cumulative Raw Returns
EMH	Efficient Market Hypothesis
FF3F	Fama and French (1993) Three Factor Model
FTSE	Financial Times Stock Exchange
IPO	Initial Public Offering
IVol	Idiosyncratic volatility
LSN	Law of Small Numbers
LSPD	London Share Price Database
MAD	Market Abuse Directive
NASDAQ	National Association of Securities Dealers Automated Quotations
NYSE	New York Stock Exchange
PEAD	Post Earnings Announcement Drift
SIC	Standard Industry Classification
TAQ	Trade and Quote
TTM	Technology, Telecommunications and Media

List of appendices

List of Tables

List of figures

Chapter One – Introduction

1.1 Introduction

This thesis is an investigation into momentum in the UK stock market and the behaviour of analysts from 1995 to 2015. The presence and profitability of momentum trading strategies over these years will be examined as well as the role that analysts' recommendations and forecasts played in shaping market behaviour. This introductory chapter outlines the background of the study, the concept of efficient markets and behavioural finance which frames the contextual setting of this study. From this, the rationale for investigating the presence of momentum in the UK stock market and the behaviour of analysts is presented. Additionally, this chapter states the research objectives and the contribution of the study. Finally, it will outline how the remainder of this thesis is structured.

1.2 Background to study

The background to the study develops the contextual setting that underpins the framework for this study. Stock market anomalies contradict the concept of market efficiency and thus an alternative model to understand how markets work is required. Any analysis of the functioning of financial markets must make assumptions about the behaviour of market participants. The desire to analyse the behaviour of financial markets and their participants has led to intense debate of standard finance theory versus an alternative option. Standard finance theory assumes in essence that investors are rational and thus investors make economic decisions whose outcomes are consistent with utility theory. Mongin (1997, p. 342) defines the expected utility theorem as when;

> The decision maker chooses between risky or uncertain prospects by comparing their expected utility values, i.e., the weighted sums obtained by adding the utility values of outcomes multiplied by their respective probabilities.

Pillars of standard finance theory include Modigliani and Miller's (1958) theorem on capital structures, the Sharpe-Lintner capital asset pricing theorem, portfolio selection theory (Markowitz, 1952), and the option pricing theorem of Fischer, Black and Scholes (1973).

Kahneman and Tversky (1979, p. 263) affirm that 'expected utility theory has dominated the analysis of decision-making under risk; it is generally accepted as a normative model of rational choice'. A central assumption of standard finance theory is that decisions are formed rationally and the cognitive biases of the investor do not affect asset prices, because errors are idiosyncratic and so average out over many agents, or that markets are sufficiently efficient to outweigh any potential for irrational investors to unduly influence the market.

Central to standard finance theory is the assumption that investors trade on the basis of rationality in an efficient market; commonly referred to as the Efficient Market Hypothesis (EMH). Within the EMH three levels of market efficiency are defined by Fama (1970); the weak form, semi-strong and strong form. The weak form of market efficiency implies future stock prices cannot be predicted in the long-run by past stock prices. The semi-strong form of market efficiency states that current stock prices are fully reflective of all publically available information. Thirdly, the strong form market efficiency implies that stock prices reflect both privately held and publically available information. Kendall (1953) had previously referred to this supposition as a random walk theory, stating that data behaves randomly with no pattern of returns discernible.

The main facet of standard finance theory challenged is the assumption of fully rational participants in the market and efficient financial markets. Alternatives to the four foundation blocks of standard finance are outlined by Statman (1999); investors are not rational under behavioural finance they are 'normal'; markets are not fully efficient but still difficult to beat; investors construct portfolios based on behavioural portfolio theory; and the asset pricing model takes cognitive errors and mental-accounting into consideration.

Thaler (1999, p. 18) argues that we can 'enrich our understanding of financial markets by adding a human element'. Furthermore, Thaler (1999) alludes to modern asset pricing theorems being generated in the presence of psychology to model the behaviour of the agents in asset pricing models, such as those devised by Barberis *et al.* (1998), Daniel *et al.* (1998) and Hong and Stein (1999). Thaler (1999, p.19) states that;

> It is possible to create a coherent theoretical model, one grounded in solid psychology and economics that can explain a complex pattern of empirical results. At the moment, no rival non-behavioural model can say the same.

The presence of anomalies in stock markets also suggests that markets are not fully efficient and certain trading strategies can 'beat' the market. Anomalies fall into two categories; calendar and fundamental. Calendar anomalies, as the name suggests refers to anomalies that occur around a certain time of the day, week, month or year. Examples of calendar anomalies include; the Weekend Effect, the January Effect, the Halloween effect, the lunar year effect and the turn-of-the month effect. Fundamental anomalies include; the momentum effect, the contrarian effect, and the size effect. As anomalies are becoming more frequent throughout financial markets, standard theories of finance struggle to explain them away with rational reasoning, thus the necessity to incorporate behavioural finance into asset pricing theories.

The momentum anomaly refers to the tendency for stocks that have performed well (poorly) in the previous period of time to continue to perform in a similar manner in subsequent periods of time; referred to as return continuation. An investment strategy that trades on the bases of momentum in stock markets is the strength-rule strategy. The strength-rule strategy takes a long position in past winners and shorts past losers. Early evidence of return continuation is documented by Cowles and Jones (1937), however, Jegadeesh and Titman's (1993) seminal study of momentum and the performance of the strength-rule strategy in US markets, is a pivotal resource and reference for several international momentum studies.

Behavioural finance incorporates aspects of investors' irrationality, such as cognitive biases and heuristics. Seldon (1912, cited in Sewell, 2010) wrote of *Psychology in the Stock Market* and argued that movement in stock prices depend significantly on the mental attitude of investors. To that effect, the expected utility theory is judged by Kahneman and Tversky's (1979) *Econometrica* paper to include a component that allows for the assumption that people underweight outcomes that are probable in comparison with outcomes that can be obtained with certainty; prospect theory[1]. Rather than measure value of overall wealth, prospect theory measures the value associated with gains and losses.

Barber and Odean (1999, p. 51) state 'one of the major contributions of behavioural finance is that it provides insights into investor behaviour when such behaviour cannot be understood under traditional theories'. Furthermore, Kahneman and Tverksy (1971) introduced the representativeness heuristic, stating that many agents draw inferences from the distribution of impressions, as opposed to outcomes as such. In this process more dramatic, and thus perhaps less likely to recur outcomes are given greater (perhaps undue) weight. This idea of representativeness is later developed by Rabin (2002) into the theory of the Law of Small Numbers (LSN). In essence, the LSN implies that the representative agent only views a small sample of all available information and makes a decision based on this observation, for them the sample is the population, reflecting the belief that the sample as it expands reflects the overall population from which it is drawn.

The study of behavioural finance is not limited to observation of individual investors but also includes the professional traders within the market. Haigh and List (2005) and Menkhoff *et al.* (2006) postulate that professional investors are subject to irrational, psychologically driven biases in investment decisions much like individual investors. Furthermore, Haigh and List (2005) affirm that the expected utility theory is not appropriate to model professional traders' behaviour; implying behavioural finance models may be more appropriate as they relax some of the assumptions of standard finance theory.

The role of brokers and analysts and the value of their recommendations and forecasts are highlighted by the early study of Cowles (1933) who finds that analysts' advice does

[1] A full discussion on prospect theory is included in section Chapter Two

contain investment value. Cowles (1933) seminal study has since been built upon by several researchers[2]. Due to the reliance on professionals within the market, their actions are under significant scrutiny and analysis. Jegadeesh *et al.* (2004) and Bird and Casavecchia (2007) state that individual and institutional investors rely heavily on the information analysts provide.

The main function of analysts is to disseminate recommendations based on the core company fundamentals and predicted forecast earnings; however, Forbes (2013, p. 2) alludes to the dual function of analysts;

> Financial analysts often wear two hats, a marketing hat for drumming up trade and hence commissions as well as a research hat for giving "independent" advice to clients regarding how best to invest their money.

The overarching aim of analysts is to add and create value in a stock by disseminating all relevant information and communicating this to the market. However, the conflicting nature of analyst work prompts debate surrounding the value and role analysts play in creating market trends. Brokers and analysts themselves may induce anomalies in stock markets by their very actions. Herding, overreaction and underreaction are all actions observable by analysts; by this very process of trading based on anomalies such as the momentum trading strategy, momentum in the wider market becomes more pronounced as investors follow the advice of analysts and mimic their investment behaviour[3]. Analysts also act as transmitters of noise and pertinent value-adding information in the market.

1.3 Rationale

The relevance of behavioural finance and its increased integration into the greater finance sphere, coupled with the persistent presence of the momentum anomaly in

[2] Other studies that find value in analysts' recommendations and forecasts include, Stickel (1995), Womack (1996), Jegadeesh *et al.* (2004) and Ryan and Taffler (2006) (see chapter three section 3.2 for further details).
[3] Evidence of analysts following momentum strategies is reported by Jegadeesh *et al.* (2004), Desai *et al.* (2008) and Bange and Miller (2004) amongst others (see chapter three section 3.7 for further details).

financial markets, provokes interest in this research topic and the desire to understand how financial markets function. Due to the perceived failure of rational models to explain the momentum phenomenon, behavioural finance is central to understanding its sustained presence in international markets.

Vayanos and Woolley (2013) state that the momentum anomaly along with the contrarian anomaly are two of the most important anomalies in finance, therefore this research aims to understand why and if momentum remains a significant financial anomaly in the UK stock market. As the time frame of study extends over several unique economic events, the perceived persistence of the momentum anomaly will be tested to observe its robustness given times of economic crises. Apart from verifying the persistent profitability of momentum trading strategies over time, this research also aims to make inferences based on any observed trends in momentum trading that may indicate possible causes of the phenomenon.

Additionally, this study aims to determine the presence of momentum across industries in the UK stock market. During the process of making investment strategy decisions, several options are considered; investment managers strive to make investment choices that offer the greatest returns whilst managing risk. Therefore industry classification plays an important role and Shynkevich (2013, p. 67) states that industry classification is;

> One of the most commonly used grouping factors to construct portfolios of stocks with homogeneous characteristics; it is common for equity portfolio managers to specialise along industries or sectors.

Investment portfolios are often constructed in the confines of industry classification as it is assumed that volatilities within industries are relatively more stable compared to firm-level volatility, as the actions or volatilities of one firm may be absorbed by the overall industry. Prior studies of industry momentum focus on US based industry momentum and European based industry momentum. For instance the seminal work of Moskowitz and Grinblatt (1999) focuses solely on momentum in the US market.

Furthermore, no significant study focuses uniquely on industry momentum in the UK stock market.

As prior literature documents, the pivotal role that brokers and analysts play in the stock market and their subsequent influence on stock prices leads to the increasing need to analyse the performance of analysts and investors' reaction to analyst behaviour. Behavioural models and discussion on cognitive psychology and bias is essential in understanding the actions of analysts in the market. Investors rely on the advice of analysts, particularly during times of economic crisis, when information may be more complex and financial markets are changing at a rapid rate. How analysts behave and frame decisions in the presence of economic crisis can have a lasting effect on stock markets and investment profitability.

Easterwood and Nutt (1999) document that analysts' underreact (overreact) to negative (positive) news. Furthermore, Easterwood and Nutt (1999, p. 1778) state;

> That analysts undereact to bad news and overreact to good news…indicate that analysts are systematically optimistic concerning the implications of new information rather than systematically misinterpreting all new information.

Arand and Kerl (2012) observe that analyst accuracy is diminished during global economic uncertainty in stock markets between October 2007 and March 2009, however investors' sensitivity to analyst output increased. Moreover, Coval and Shumway (2005) find the professionals being subjected to the same behavioural bias of individual investors, prompting the questions; are analysts afflicted by behavioural bias such as overreaction and optimism in their output and does their behaviour oscillate during times of economic crisis?

In addition, Bange and Miller (2004) and Desai *et al.* (2000) report that analysts engage in momentum trading i.e. recommending investors to purchase (sell) stocks that have previously performed well (poorly). When analysts engage in momentum trading this exacerbates momentum, as individual investors mimic the behaviour of analysts thus further driving the price of the stock.

1.4 Research objectives

Based on the contextual setting outlined previously by the discussion of behavioural versus standard finance, this thesis endeavours to answer a number of key research questions in relation to momentum in the UK stock market and the perceived behaviour of analysts during the time period 1995 to 2015. In relation to the subject of momentum this thesis aims to determine its presence in the UK stock market overall, its prevalence in specific market states and its sustainability as an investment technique throughout the years. Overall it aims to examine the ecology of stock market momentum drawing upon the idea of a 'behavioural scissors' of cognition of context (Simon, 1990).

Additionally, the role of analysts in the market will be investigated, most notably their behaviour during times of economic stress and any potential flight of analyst guidance during times of economic strife. Therefore, the following research goals are outlined;

1) Is momentum present in the UK stock market between 1995 and 2015 and if so is it possible to make abnormal returns by following the strength-rule strategy?
2) Is momentum more pronounced in industries?
3) Is momentum more pronounced during certain time periods?
4) Were analysts' recommendations accurate during times of economic crises?
5) Did analyst behaviour exacerbate the financial crises?

1.5 Contribution

This study contributes to the existing field of research in a number of aspects. Firstly, the nature of the study focuses on the UK stock market specifically. While many studies have included analysis of the UK stock market along with several other markets or in comparison to other markets, few studies have focused specifically on the UK market.

Furthermore, this study uses a combination of various rank and hold combinations of the strength-rule strategy, allowing for in-depth analysis of momentum in the UK stock market and the identification of the most appropriate length of investment strategy.

Secondly, the time period of analysis in this study (1995 to 2015) includes several unique economic events such as the Internet bubble, the Northern Rock crisis and the global financial crisis. The behaviour of markets and market participants during these time periods will be isolated in order to draw inferences in relation to stock market behaviour. Dividing the overall time period into relevant sub-periods generates a more in-depth discussion surrounding the performance of momentum in given market states, eliminating any potentially misleading conclusions that may be a result of momentum and/or market behaviour in specific periods of time only.

Thirdly, this study differs significantly from prior studies, as it includes analysis of the performance of industry momentum strategies in the UK market. Evidence and discussion of industry momentum in the UK stock market has been neglected in prior studies. This study is unique in that it evaluates the performance of both individual stock and industry momentum strategies during the same time periods, allowing for comparison between such strategies and the performance of each strategy, given certain market conditions.

Fourthly, the analysis of the behaviour of professionals in the market is of crucial importance given the reliance on their advice. Such professionals might be regarded as the 'smart money' in the market. If they cannot get it right who can? During times of economic uncertainty when financial positions are rapidly changing the role of brokers and analysts is never more central. It is during difficult economic times that financial markets require analysts to be fair and relatively accurate as to not exacerbate a difficult economic situation. This study provides insights into how the 'professionals' performed during two key economic crises; the Internet bubble and the more recent global financial crisis.

This study is of interest to those in the academic field and front-line investors as the findings may identify a profitable investment strategy for the UK stock market and how this strategy performs during times of economic crises. Furthermore, by analysing the behaviour of brokers and analysts during times of economic crises, conclusions can be drawn on the reliability of their advice; thus in similar situations in the future investors will be able to make an informed investment decision knowing how analysts behave during economic crises.

Using the Fama and French (1993) three-factor model as a return generating model incorporates appropriate variables for risk including the size and value premium. The three-factor model is more sophisticated than other return generating models and alleviates some of the criticisms levied at the Capital Asset Pricing Model. Additionally, for the analysis of momentum several rank and hold combinations are used, allowing for the more detailed interpretation of returns. The long holding period of 24 months also enables conclusions to be drawn on any reversal of trends after a certain period of time.

1.6 Structure of thesis

The remainder of this thesis is organised as follows; chapter two presents literature relating to the momentum anomaly; including its origins of discussion in literature, methods developed to determine its presence as well as a comprehensive assessment of the presence and profitability of momentum in international markets. Furthermore, chapter two outlines the purported causes of momentum, with discussion centering on the behavioural and rational explanations of the phenomenon. A discussion on its presence across industries is also included in section 2.6. Evidence of its reversal is documented in section 2.8.

Chapter three delineates the research and literature surrounding the role and impact of brokers and analysts in the market place. Their role in creating momentum in markets as well as the impact of their research output has on markets is outlined. Additionally, the conflicted nature in which analysts construct forecasts and recommendations is addressed as well as the regulatory response to such conflicts. Brokers and analysts are not immune to the same behavioural biases individual investors are subjected to and this concept is also scrutinized in chapter three.

Chapter four provides details of the data collection process and the method of analysis used to answer the research questions outlined. All stocks listed on the FTSE100 index between 1995 and 2015 are included in the sample. Analysts' recommendations and forecasts during the Internet bubble period and global financial crisis period are analysed to determine the accuracy and veracity of analyst output during times of economic crisis.

Chapter five reports on the presence of the momentum anomaly in the UK stock market between 1995 and 2015; overall momentum is present in the UK stock market, signifying a level of market inefficiency in the UK. The strength-rule strategy performed best during the Internet bubble period with returns declining towards the latter years of the study. Chapter five also documents the presence of industry momentum in the UK stock market; industry returns are not as large as individual momentum returns. In addition to reporting on evidence of momentum in the UK market, chapter five also documents that analysts' recommendations contain investment value in the years surrounding the Internet bubble. Evidence of deterioration in the accuracy of analysts' recommendations is also presented in chapter five.

Chapter six provides detailed and in-depth discussion on the main findings of the study, including; the better performance of individual momentum strategies in all time periods compared to industry momentum strategies. Contrary to prior literature, evidence of this study implies that a short rank and long hold period is the optimal strategy for momentum investing. Chapter six, section 6.3 discusses the levels of optimism in analysts' recommendations and the reluctance to issue negative recommendations. Chapter six, section 6.4 discusses the investment value contained with analyst output; notably analysts' recommendations during the global financial crisis period were not accurate.

Chapter seven, the concluding chapter, restates the main research findings and addresses the implications of the findings. The contribution and limitations of the study are outlined. Chapter seven also highlights areas of possible further research.

1.7 Chapter summary

This chapter provided an introduction to the study and a synopsis of the ongoing debate between standard and behavioural finance schools of thought. Understanding the core concepts of both is pivotal to understanding the nature of markets and its participants. The rationale for choosing the topic, as well as outlining the research questions sought to be answered in this study are all included in this introductory chapter. The potential contribution of this study was highlighted and the structure of the remainder of the thesis presented.

Chapter Two – Momentum

2.1 Introduction

This chapter synthesizes the theory relevant to the discussion of the momentum anomaly. The definition of the anomaly is firstly addressed and evidence of its presence across international stock markets is reviewed. Additionally the main causes of the anomaly are presented, broadly split into two sections; section 2.4 addresses the rational explanations put forward to explain momentum in stock markets and section 2.5 outlines the main behavioural causes of the anomaly. The presence of momentum across industries is documented in section 2.6, section and section 2.8 addresses evidence of apparent reversal of the anomaly.

2.2 Momentum

The consensus of previous literature on stock market anomalies is that the momentum anomaly is a persistent anomaly in financial markets. Studies document the existence of momentum in a vast number of countries internationally, across various instrument types and during varying time periods (see section 2.2.1). The existence of the momentum anomaly is largely accepted, with most notably Eugene Fama (1998) conceding that the momentum anomaly is 'above suspicion' (Fama, 1998, p. 304) however the causes of momentum remain a controversial debate (Herberger *et al.*, 2009).

Although definitions of momentum vary slightly, generally momentum can be defined as continuation or positive serial correlation in returns, i.e. stocks that performed well in the past will continue to do so in the future (Mansouri *et al.*, 2012). Daniel and Moskowitz (2013) state that a momentum strategy is a belief that past returns will predict future returns, and thus a momentum strategy typically involves buying past winners and shorting past losers.

Similarly, Burton Malkiel (2000) in the *Wall Street Journal* described momentum trading as the practice of purchasing stocks that have experienced large gains in the recent past relative to the overall performance of the market. Section 2.2.1 amasses the key evidence of the momentum anomaly across international stock markets.

2.2.1 International evidence

There is a plethora of evidence of momentum in financial markets internationally. Early research by Cowles and Jones (1937) and Levy (1967), document that following an increase of the market over a day, week, month or year, the market continues to increase for subsequent periods of the same length. Although Cowles and Jones (1937) find continued positive correlation, daily and weekly time periods are judged too short to cover transaction costs and only modest profits are earned using a holding period of one month.

In reference to the momentum anomaly, the strength-rule strategy is a method adopted by investors to generate excess returns in the presence of momentum in markets. The strength-rule strategy refers to the process of buying stocks that have performed relatively well in the previous three to twelve months and selling stocks that have underperformed in the same period.

In a seminal paper, Jegadeesh and Titman (1993) employ the strength-rule strategy to determine if momentum is present in US stocks for the time period 1965 to 1989. At the beginning of each month t, securities are ranked based on their performance in the previous J months (three, six, nine or twelve months) and held for a period of K months (three, six, nine or twelve months). These securities then form ten equally-weighted portfolios. The highest return portfolios are referred to as 'winners' and the lowest return portfolios as 'losers'. To increase the robustness of their strategy, Jegadeesh and Titman (1993) use a second method to form a portfolio, whereby a week is skipped between the formation and holding period to avoid the bid-ask spread price costs and lagged reaction effects. Jegadeesh and Titman (1993) find that the optimal strategy consisted of ranking stocks based on the twelve months performance and holding ‘winners’ and selling ‘losers’ for three months, with a return of 1.31 per cent per month generated. Additionally, returns reported by Jegadeesh and Titman (1993) are not generated by short-selling.

Furthermore, in an extension of their earlier study, Jegadeesh and Titman (2001) find that momentum profits continue to exist into the 1990s, suggesting that their original findings are unlikely to have been the result of data-snooping bias. However, it is argued by Lesmond *et al.* (2004) that the momentum profits reported in Jegadeesh and Titman (1993) are insignificant once transaction costs are accounted for.

Several other studies concur with the findings of Jegadeesh and Titman (1993) that the strength-rule strategy can be profitable for US stocks including; Grundy and Martin (2001) who report monthly returns of 0.76 per cent for the NYSE and AMEX markets between 1926 and 1995. Hammami (2013) observes that momentum appears in US markets during good periods, i.e. when expected market risk is low. Chan *et al.* (1996), George and Hwang (2004) and Lee and Swaminathan (2000) also document evidence of momentum in the US market.

Previous evidence of momentum has not been confined to US markets; in a study of European markets, Rouwenhorst (1998) observes that momentum is a phenomenon in 12 European markets (Austria, Belgium, Denmark, France, Germany, Italy, the Netherlands, Norway, Spain, Sweden, Switzerland, United Kingdom) for the years 1980 through to 1995 and reports that momentum profits of approximately one per cent per month can be earned by selling medium-term past ‘winners’ and shorting medium-term past ‘losers’. Similarly, Doukas and McKnight (2005) report that momentum is present during the years 1988 to 2001 in eight out of thirteen European stock markets included in their study.

Evidence of momentum in European stock markets is documented by van Dijk and Huibers (2002). Patro and Wu (2004) observe momentum in a multi-country study covering 1979 to 1998. Further evidence in support of momentum is reported in Balver and Wu (2006) for developed markets and Bird and Whitaker (2003) for European markets between 1990 and 2002. Hu and Chen (2011) report momentum profits are attainable in a study of 48 countries between 1999 and 2007; specifically the greatest momentum profit is achieved in the ninth month of a holding period following a ranking period of one or three months. Also, Fong *et al.* (2005) report momentum in a study of 24 countries between 1989 and 2001. Evidence of momentum in Canadian stocks is reported by Hou and McKnight (2004).

Specifically in the German stock market, Glaser and Weber (2003) report momentum is evident between 1988 and 2001 particularly for stocks with a higher turnover rate. In an investigation of momentum in Irish shares, O'Keeffe and Gallagher (2014) observe a persistent presence of momentum over a 24 year period, specifying momentum is particularly evident during non-crisis periods (pre 2007). However, O'Keeffe and Gallagher (2014) find that momentum profits are reduced during times of economic crisis in Ireland (post 2007).

Rey and Schmid (2007) investigate momentum in the Swiss market and find momentum is present while focusing on the largest blue chip stocks. Muga and Santamaria (2007) report evidence of momentum in the Spanish market although it disappears after the 1997 crisis. Forner and Joaquin (2003) also report evidence of momentum in the Spanish market.

As the UK main market consists of relatively large firms and is classed as a similarly developed market, evidence of momentum in UK markets is similar to that of US markets. In an observation of the UK market between 1955 and 1996, Hon and Tonks (2003) note that momentum is a feature over short to medium-term time horizons. Upon further examination of their data, Hon and Tonks (2003) report that momentum in the overall time period (1955-1996) is almost entirely driven by the presence of significant momentum in the latter time period only (1977-1996). Hon and Tonks (2003) suggest that the presence of momentum is correlated with market volatility variations and thus may be only a factor for certain periods of time.

Similarly, Liu *et al.* (1999) observe momentum in the UK stock market during the 1977 to 1998 period, and state results remain robust after accounting for systemic risk, size and book-to-market factors. Chelley-Steely and Siganos (2006) document momentum in the UK between 1975 and 2001, with an average monthly return of 0.55 per cent observed.

Further investigations into momentum in the UK market are conducted by; Liu *et al.*, (1999) and Siganos (2010) who report similar evidence of momentum over varying time periods. Additionally, Galariotis *et al.* (2007) observe momentum in the London Stock Exchange between 1964 and 2005, likewise Eilis and Thomas (2004) report medium-term momentum in the FTSE350 between 1990 and 2003. Clare and Thomas (1995) and Dissanaike (1997) also report evidence of momentum in the UK market.

Evidence of momentum in less developed or emerging markets is also documented, with Swinkles (2004) asserting that both emerging and developed markets exhibit similar momentum tendencies. Momentum in emerging markets such as Thailand, Malaysia, Brazil and India is documented by Naranjo and Porter (2007). Furthermore, van der Hart *et al.*, (2003) report momentum in several emerging markets including; Morocco, Nigeria and Sri Lanka.

Internationally, momentum is reported in several markets. Chan *et al.* (2000) finds statistical evidence of momentum in 25 countries. In the Australian market, Hurn and Pavlov (2003) and Demir *et al.* (2004) observe significant momentum as do Schneider and Gaunt (2012). Drew *et al.* (2007) also document momentum in the Australian stock market between 1998 and 2002; Phua *et al.* (2010) and Durand *et al.* (2006) report similar findings.

Evidence of momentum is also found in Asian markets. Ramiah *et al.* (2011) find evidence of momentum in Asian markets between 1992 and 2006; similarly, Chui *et al.* (2010) observe momentum in Asian markets between 1980 and 2003. McInish *et al.* (2008) observe momentum in the Japanese and Hong Kong markets; conversely, Cheng and Wu (2010) find momentum profits insignificant in Hong Kong. Ryan and Curtin (2006) also report weak evidence of momentum in Asian markets. Du *et al.* (2009) similarly observe weak evidence of momentum in Taiwan and Thai markets.

Ryan and Curtin (2006) examine momentum in Pacific-Basin countries and find 'unrestricted momentum strategies' are not profitable, using a six-month rank and six-month hold formation between 1991 and 2000. They further state that although winners outperform losers, as expected, they are statistically insignificant. Out of the 16 momentum trading strategies examined, fourteen report negative returns, ten of which are statistically significant. Ryan and Curtin (2006, p.38) assert that the 'results represent challenges to those researchers trying to reconcile within a unified framework short-term momentum and long-term overreaction in equity markets'.

Alwathaninani (2012) investigates the possibility of two mis-pricing effects, namely the momentum effect and its subsequent reversal, and if the two phenomena are empirically connected. Alwathaninani (2012) finds that a zero-investment strategy that holds a long position on consistent 'winners' and a short position on consistent 'losers' earns significant monthly returns in the US market. Barber *et al.* (2009) use tick-by-tick transaction level data gathered from the TAQ (Trade and Quote) and ISSM databases to find four key results for the years 1983 to 2001. First, order imbalance exists based on buyer and seller initiated small trades. Second, individual investors tend to exhibit characteristics of herding. Third, stocks bought in week one earn strong returns in the subsequent weeks, with the pattern continuing for three to four weeks after which it reverses for several weeks. Finally, small-cap stocks have positive contemporaneous returns when measured over a one-year time period.

Novy-Marx (2012) documents the relevance of the length of test period to momentum returns. Novy-Marx (2012) reports that momentum is most profitable following a test period of intermediate-length, between twelve and seven months, prior to portfolio formation period. A test period length in excess of twelve months prompts an 'abrupt' drop-off in the size of momentum profits. Additionally, very short test period lengths have an equally negative effect on momentum profits.

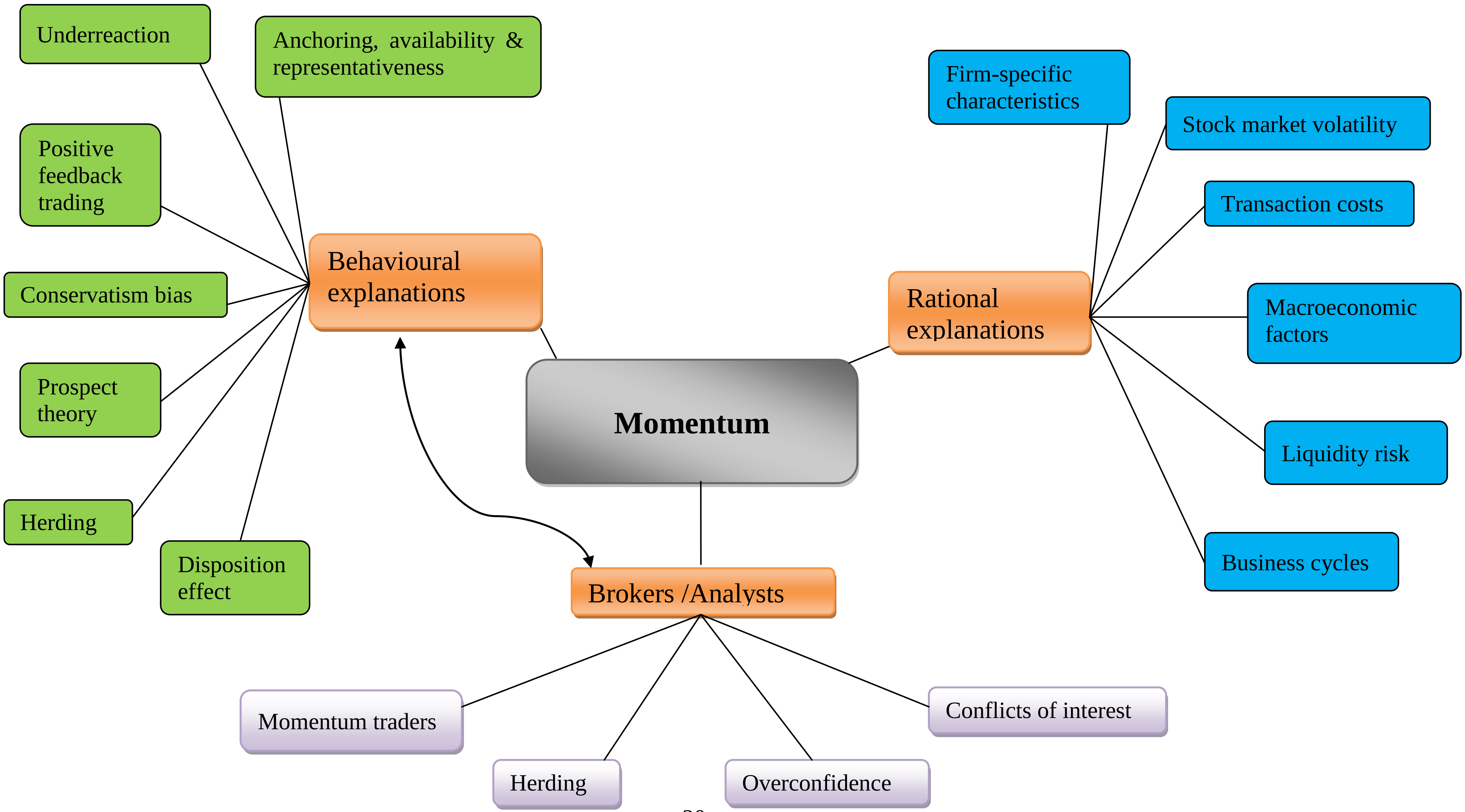
Evidence also suggests that momentum is not limited to stock returns but is present in the real estate market (Genesove and Mayer, 2001); company stock options (Heath *et al*,1999); futures market (Locke and Mann, 2004); currencies (Okunev and White, 2003), exchange traded funds (Moskowitz *et al.*, 2012) and bonds (Asness *et al.*, 2013).

2.3 Causes of momentum

Although the presence of momentum has been established to exist in several international stock markets, a debate is ongoing as to what are the principal causes of the phenomenon (Herberger *et al.,* 2009). In the subsequent years since Jegadeesh and Titman's seminal study many have attempted to identify the key causes of momentum. Both rational and behavioural causes of momentum have been articulated as possible causes and are discussed in the following sections. Figure 2.1 illustrates the main causes of momentum; both rational and behavioural.

Figure 2.1 includes the key rational and behavioural causes of momentum that are discussed in prior literature and also acknowledges the role analysts play in driving momentum within a market. The link between analysts and momentum is highlighted by prior studies such as Bange and Miller (2004) and Desai *et al.* (2008). Analysts are also subjected to the same behavioural biases as investors and thus their actions may be comprised by such behavioural actions, in turn, their actions may pronounce momentum in certain circumstances.

Figure 2.1 Causes of momentum



Source: Authors own

2.4 Rational explanations

Many of the rational explanations put forward to explain momentum focus on flaws in the research design or methodology, citing issues such as ignoring the effect of transaction costs or errors in the collection and inclusion of data. Neoclassical economists believe that momentum is a result of rational compensation for risk or liquidity premium (Fuertes *et al.*, 2009). Several rational models have been developed to explain momentum (Berk *et al.,* 1999; Johnson, 2002 and Albuquerque and Miao, 2010).

2.4.1 Macroeconomic factors, stock market volatility and business cycles

It is suggested in prior literature that macroeconomic factors influence stock returns and have a fundamental impact on momentum in markets (Chelley-Steeley and Siganos, 2004). Bacmann *et al.* (2001) find that a significant link exists between macroeconomic factors and momentum profits. Karolyi and Kho (2004) also find that momentum profits can be explained by macroeconomic instrumental variables. However, Griffin *et al.* (2003) find international evidence of significant momentum during both good and bad economic times.

Market cycles such as bull markets and bubbles in the economy impact the level and profitability of momentum. Signos and Chelley-Steeley (2006) examine the profitability of momentum strategies following bull and bear market conditions in the London Stock Exchange and find that momentum returns are more pronounced following a downturn in market conditions. Conversely, Conrad *et al.* (1999) report evidence to suggest that momentum profits are higher in times of bullish market conditions. Moskowitz and Grinblatt (1999) ascertain that momentum strategies work best in recessionary times. Cheng and Wu (2010) note that upon including macroeconomic variables, momentum profits become insignificant in Hong Kong.

Market volatility and business cycles can change greatly over time. The well-documented financial crises of late 2008 and the subsequent economic strife impacted significantly on market volatility. Motivated by the period of high volatility across markets in late 2008, Wang and Xu (2015) examine the impact of volatility on the profitability of momentum strategies. They conclude that momentum strategies perform poorly in the early part of 2009, which would have been during a period of sustained market turmoil. Additionally, they document that historically, momentum strategies have performed poorly following similar instances of market volatility, specifically in the early 1930s and mid-1970s. Chordia and Shivakumar (2002) report the profitability of momentum strategies may be affected by business cycles.

Griffin *et al.* (2003) reports that momentum profits are also stronger during down markets in Africa, Asia, Europe and the US. Conversely, in a study of US markets, Cooper *et al.* (2004) document more pronounced momentum following up markets between 1929 and 1995. However, Geczy and Samonov (2013) affirm that following the financial collapse in 2008, momentum profits collapsed in the US 'creating a large ripple in investment portfolios that use that strategy' (Geczy and Samonov, 2013, p. 2). Similarly, Grobys (2014) document that 'momentum crashes' occur following exceptionally large market declines, with large statistically significant negative returns reported following the economic recession of 2007 to 2009.

2.4.2 Transaction costs and short-selling selling

The level and significance of momentum profits may be eroded once transaction costs are accounted for. Bernard and Thomas (1989) suggest that transaction costs in general may inhibit the response of investors to new information. Moskowitz and Grinblatt, 1999; Grundy and Martin, 2001; and Lesmond *et al.,* 2004, suggest that in order for momentum trading strategies to be profitable high portfolio trades must take place. Due to the necessity for high portfolio turnover, transactions costs may well be prohibitive (Sadka, 2005).

Lesmond *et al.* (2004) find that strength-rule strategies require frequent trading and stocks which generate momentum have disproportionately high transactions costs, absorbing any possible excess returns; Hanna and Ready (2005) reach similar conclusions. Lesmond *et al.* (2004) go further to suggest that transaction costs are under-estimated in earlier studies of momentum such as Jegadeesh and Titman (1993). Lesmond *et al.* (2004) further argue that in general transaction costs for large capitalisation stocks can be estimated to vary between one and two per cent, whereas, smaller capitalisation stocks incur significantly larger transaction costs of between five and nine per cent. Korajczyk and Sadka (2004) use four approaches to estimate transaction costs and conclude that transaction costs are independent of firm size and do not explain momentum profits.

The length of holding period may also influence the level of transaction costs incurred; Agyei-Ampomah (2007) find that a holding period in excess of six months can generate abnormal returns. Rey and Schmid (2007) ascertain that significant abnormal returns can be generated by selecting large capitalisation companies for inclusion in an investment portfolio. Furthermore, Siganos (2010) assert that the number of firms included in the winner and loser portfolios can have an impact on the level of transaction costs incurred during trading. Herberger *et al.* (2009) use various rank and holding periods and conclude that momentum strategies are still profitable after transaction costs.

The short selling component of momentum trading may also increase transaction costs. Geczy *et al.* (2002) find that transaction costs incurred due to short selling are not sufficient to eliminate momentum profits. Furthermore, Griffin *et al.* (2005) observe that momentum profits can be generated without necessarily holding a short position in an investigation of over 40 countries. Fong *et al.* (2005) report similar conclusions from an investigation of momentum strategies in 24 countries between 1989 and 2001, and report that for most combinations of rank and holding periods, momentum returns are still possible by longing the winner portfolio only.

Ali and Trombley (2006) argue that momentum returns are largely made up of ‘loser’ portfolios and short-sale restrictions prevent excess returns. During times of financial crises and market turmoil, restrictions on short-selling are often implemented to prevent excessive trading and certain market participants gaining an unfair advantage. Moreover, Barber and Odean (2008) state that only 0.29 per cent of individual investors engages in the practice of short-selling.

2.4.3 Liquidity risk

The level of liquidity risk varies across industries and momentum may be merely a reward for increased liquidity risk. Sadka (2006) reports that over 80 per cent of cross-sectional variation in momentum profits is directly attributable to liquidity risk. Pastor and Stambaugh (2003) note that a significant proportion of momentum profits are attributable to liquidity risk, with Chang (2005) finding similar percentages of momentum profits explained by liquidity risk.

2.4.4 Firm-specific characteristics and seasonality

Smaller firms tend to exhibit greater levels of momentum, possibly due to small firms having less institutional owners and it is firm-specific characteristics such as this that result in momentum (Griffin *et al.*, 2003). For instance, Grinblatt and Moskowitz (2004) find that firms with high trading volume tend to show greater signs of momentum, as do firms with less institutional ownership. Additionally, firms with high growth have a certain level of expected returns; hence momentum is prevalent due to ‘winner’ stocks having higher expected returns than ‘loser’ stocks (Johnson, 2002). Cohen *et al.* (2002) also assert that stocks with low levels of institutional holdings exhibit higher levels of momentum.

Similar to this, Berk *et al.* (1999) argue that a consistency in expected returns among firms may increase the prevalence of momentum, as investors come to expect a certain level of returns they continue to invest in the stock, creating momentum. Alwathainani (2013) examines the consistency in quarterly earnings and observes that consistent growth in quarterly earnings creates financial momentum. Grinblatt and Moskowitz (2004) find that winner consistency is particularly important and 'achieving a high past return with a series of steady positive months appears to generate a larger expected return than a high past return achieved with just a few extraordinary months' (Grinblatt and Moskowitz, 2004, p. 542).

Johnson (2002) asserts that rational explanations of momentum are plausible; employing a 'simple, standard model of firm cash-flows discounted by an ordinary pricing kernel can deliver a strong positive correlation between past realized returns and current expected returns' (Johnson, 2002, p. 585). Key to Johnson's model is stochastic expected growth rates of the firm. The rational model of momentum strategies involves discounting cash-flows by a pricing kernel to generate a relationship between past realised returns and future cash-flows.

Arena *et al.* (2008) report that momentum investing in high idiosyncratic volatility stocks (IVol) yield higher returns. Using a sample of US stocks over a long period of time (1965 to 2002), they find that a positive relationship exists between momentum and high idiosyncratic volatility stocks; additionally high IVol stocks show a tendency to reverse quicker.

Fu and Wood (2010) examine how seasonality might affect momentum in Taiwan; they find an annual cycle present with momentum profits peaking in May to July after turning positive in March; negative returns or low positive returns are recorded during September to December. However, Jegadeesh and Titman (1993) and Grinblatt and

Moskowitz (2004) find that momentum profits are higher in December. Grundy and Martin (2001) report losses during January for the majority of years in their sample.

2.5 Behavioural causes

Behavioural explanations have been developed to explain momentum and eliminate some of the perceived limitations associated with rational explanations. Behavioural finance (BF) adds a psychological non-rational dimension to explain market behaviour. Momentum is seen as a key feature of BF and Du (2012) allude to the expanse of literature that focuses on behavioural explanations of the momentum phenomenon, such as underreaction, conservatism bias and overconfidence.

In recent years, the focal point of many studies has shifted from the reporting of momentum in any given market, to the discussion of possible causes of momentum in that market, with many of the behavioural explanations of momentum centering on experimental cognitive psychology (Xiang *et al.*, 2002). The level of control that investors have over their investment decisions differs greatly from individual investors to professional investment fund managers; the level of skill and resources at the disposal of investors also differs considerably. Strahilevitz *et al.* (2011) details the psychology behind investing decisions, particularly for individual investors who have a considerable amount of control over their investment decisions. The aforementioned work of Strahilevitz *et al.* (2011) alludes to the possibility of individual investors lacking the skills required to accurately foresee the full impact of their investment decisions on their portfolio returns. However, individual investors are acutely aware of the emotional impact of their investment choices.

It is this lack of reason that leads to the greater need to include facets of BF in the discussion of any stock market anomaly. Swinkles (2004) suggests that the irrational behaviour of investors concerns human decision-making processes and the lack of plausible risk-based explanations impels research to focus on behavioural explanations. Fong *et al.* (2005, p.89) state ‘that the search for rational asset pricing explanations for the momentum effect may be a futile one’. Moreover, it is safe to assume that differences in decision-making will differ greatly amongst investors and investors from certain cultures may respond differently to risk (Chui *et al*, 2010).

2.5.1 Underreaction

The process of underreaction, i.e. a delayed price reaction, is one element of BF utilized to explain momentum. Investors may underreact to news announcements and firm- or market-specific information for several reasons leading to a delayed price reaction resulting in momentum. The reaction of investors to good and bad news can differ significantly, with bad news often ignored as it does not reaffirm investors’ original thought regarding the stock (Ashley, 1962).

Post earnings announcement drift (PEAD) is a prevalent example of underreaction in markets. Such is the impact of earning announcements on prices that Fama (1998, p.286) labelled PEAD the ‘grandaddy of underreaction events’. Ball and Brown (1968) were one of the first to hypothesise the effect that earning announcements have on prices and state that prices tend to follow an upward drift pattern following ‘good’ news and a downward drift following ‘bad’ news, similar to earlier evidence by Ashley (1962). Foster *et al.* (1984) also find evidence of earnings announcements impacting stock prices and conclude that PEAD is negatively correlated to firm size.

Bernard and Thomas (1989) define the practice of prices drifting after earnings announcements (PEAD) as arising from two distinct categories; the first category relates to investors’ ability to assimilate available information in a timely manner, thus their delay in responding to new informaiton. Secondly and less likely the second category relates to the risk model. The capital asset pricing model (CAPM) fails to fully adjust for risk, because of either incompleteness in the model or incorrect information components or some combination of both. This implies that firms with unexpectedly high or low earnings become more or less risky based on some unknown dimension resulting in the unexpected earnings.

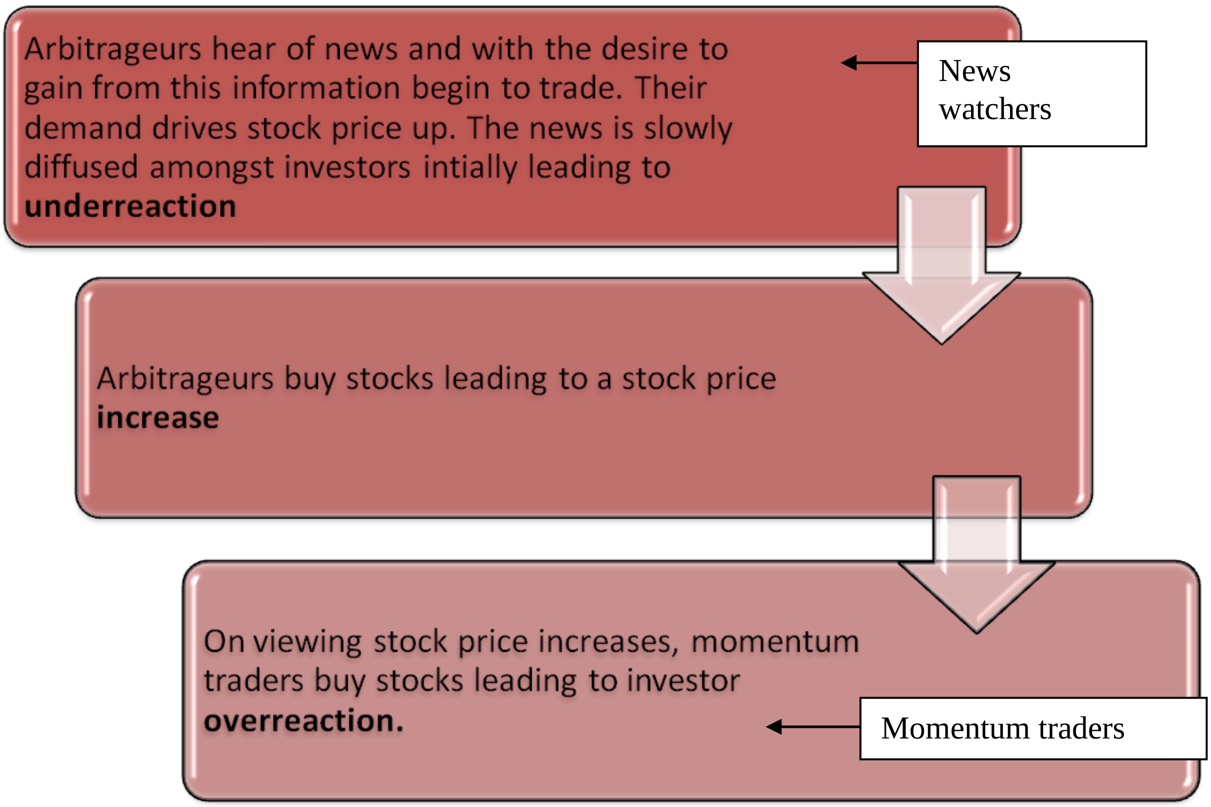
Ball (1988) argues that trading strategies based on expected earnings might generate profits due to the shortcomings of the CAPM; this result was later fortified by Ball *et al.* (1988) and Foster *et al.* (1984). While misspecifications with the CAPM are easier to explain, the first reason isolated as a cause of PEAD and subsequent underreaction is a more difficult aspect to explain (Bernard and Thomas, 1989). The delay of investors' response to earnings announcements (underreaction) is damaging to market efficiency and an antagonist to the EMH (Lev and Ohlson, 1982). One possibility proposed by Bernard and Thomas (1989) for this investor underreaction is that investor response is constrained by transaction costs. Moreover, investors tend to only realise the consequence of PEAD once the future earnings are realised, thus forgoing the opportunity for abnormal gains to be made from trading. Momentum being a subset of PEAD, Jackson and Johnson (2006) state that both momentum and PEAD are caused by the same underlying condition; changes in expected earnings (Jackson and Johnson, 2006).

In a summary of past empirical evidence, Sadka (2005) reports that prices do drift after earnings announcements, and PEAD is significantly related to the amount of private information about a given firm (Francis *et al.,* 2005; Vega, 2004). However, Chordia and Shivakumar (2002) posit that PEAD is a result of macroeconomic factors and not investor underreaction.

The level of underreaction to news may be dependent on the rate of information diffusion throughout the market. Hong and Stein (1999) developed a model to illustrate the co-existence of under and overreaction in the market based on the theory of information diffusion. Hong and Stein's (1999) study focuses on the interaction of traders within markets rather than the psychology of the representative agent. It makes the assumption that investors are constrained by bounded rationality, i.e. investors only process one facet of the publically available information.

Hong and Stein's (1999) model is based on two types of investors within the market structure; news watchers and momentum traders. The news watchers observe and react to information regarding the fundamentals of the company; the momentum traders observe changes in stock prices and adjust their demand for the given stock in accordance with price changes. Figure 2.2 is a representation of their model.

Figure 2.2 Hong and Stein (1999) Information diffusion; under and overreaction



Source: Authors own

The key to understanding Hong and Stein's (1999) model is slow diffusion of information amongst investors and hence the subsequent underreaction to news. The model predicts that stocks with low information and analyst coverage are associated with pronounced momentum as a result of investor underreaction. Low analyst coverage implies that information takes longer to reach investors leading to subsequent underreaction and pronounced momentum. Moreover, Savor (2012) states that investors both over and underreact; under-reacting to fundamental news and over-reacting to other news.

The theoretical predictions of Hong and Stein's (1999) model are confirmed in a later study by Hong *et al.* (2000), who report similar findings regarding low analyst coverage inducing a more pronounced momentum effect. Similarly, Hong *et al.* (2000) report that gradual diffusion of information throughout the markets results in the delayed reaction of stock prices, as it takes longer for the critical market information to reach the final investor in the information chain. Zhang (2008) reaches similar conclusions and postulates that factors such as analyst coverage, firm size and cash-flow volatility, affect the rate of information diffusion throughout the market and subsequent stock-price reaction. Additionally, Doukas and McKnight (2005) investigate the cause of momentum in thirteen European stock markets and conclude that momentum is partly due to the gradual diffusion of information amongst investors.

As seen from the aforementioned literature, stocks with low analyst coverage often exhibit stronger evidence of momentum; hence analysts and momentum are inextricably linked. Furthermore, the recommendations and forecasts analysts issue signal news within the market; not only is the reaction of investors to this news important, but so is the process of analysts forming their recommendations and forecasts. Indeed, analysts themselves may underreact to new information and fail to incorporate it in their recommendations and forecasts. Chan *et al.* (1996) report underreaction by analysts induces momentum in stock prices. Chan *et al.* (1996) further state that forecasts are revised slowly, thus new information is dispersed slowly throughout the market, leading to further underreaction by investors in the wider market. Moreover, analysts may be slow to revise downwards forecasts and recommendations due to several conflicting issues, thus leading to underreaction. The conflicts analysts face will be discussed in detail in Chapter three, section 3.3.

2.5.2 Conservatism bias

As stated previously, investors can underreact to information for several reasons, but how investors react to the information upon receiving it also differs; the premise that investors react in a timely and appropriate manner is not always the case. Conservatism bias sometimes referred to as confirmation bias refers to investors insufficiently adjusting their priors upon gathering new information; it is a form of selective thinking. Investors are reluctant to adjust their beliefs upon receiving new information and when re-adjustment does occur it is often insufficient leading to underreaction. Montier (2002) argues that often investors may seek information that confirms or supports their existing views, thus inducing underreaction amongst investors as they fail to fully adjust appropriately for new information (conservatism bias). This induced underreaction subsequently leads to prominent momentum.

Barberis *et al.* (1998) develop a model that proposes that repetition of earning announcements are largely unnoticed by investors (conservatism bias); as a result the price impact of these earnings announcements is not incorporated into stock prices in a timely manner (underreaction). The core tenet of the Barberis *et al.* (1998) model is that investors believe that a good trend in a firm’s earnings announcements is representative of future performance. In other words, investors insufficiently adjust their priors upon gathering new information leading to initial underreaction, whilst simultaneously investors form a representative bias leading to a delayed overreaction, placing too much weight on current earnings in an attempt to predict future earnings (Jegadeesh and Titman, 2001).

Although Doukas and McKnight (2005) find that momentum is in part attributable to slow information diffusion, another contributory factor is conservatism bias. The complexity of the task for investors may also impact on their processing of information. Edwards (1968, cited in Conor *et al.* 2010) suggest that conservatism bias could be an experimental artefact; the more complex the task the increased difficulty people have in processing information leading to performance errors

2.5.3 Overconfidence

Another key behavioural theory proposed to explain momentum is the level of confidence amongst investors, particularly when this confidence becomes overconfidence. Again, the complexity of the security selection process may impact on the level of overconfidence in markets as investors overvalue their knowledge and fail to adjust adequately for risk (Nofsinger, 2001).

How does overconfidence impact on the prevalence of momentum in markets? Daniel *et al.* (1998) develop a behavioural model based on the premise that overconfidence and self-attribution bias of investors induces momentum within stock prices; similar to Hong and Stein (1999), they find that at certain times both over and underreaction co-exist in the model. The model of Daniel *et al.* (1998) predicts that investors who are well informed are overconfident in the private information that they receive and trade based upon this information. The release of information that confirms privately held beliefs will further increase their confidence in the previously held information, inducing market overreaction. The self-attribution element of the model relates to investors attributing success to their own ability and any failure is attributed to some external factor beyond their control (Shefrin, 2002).

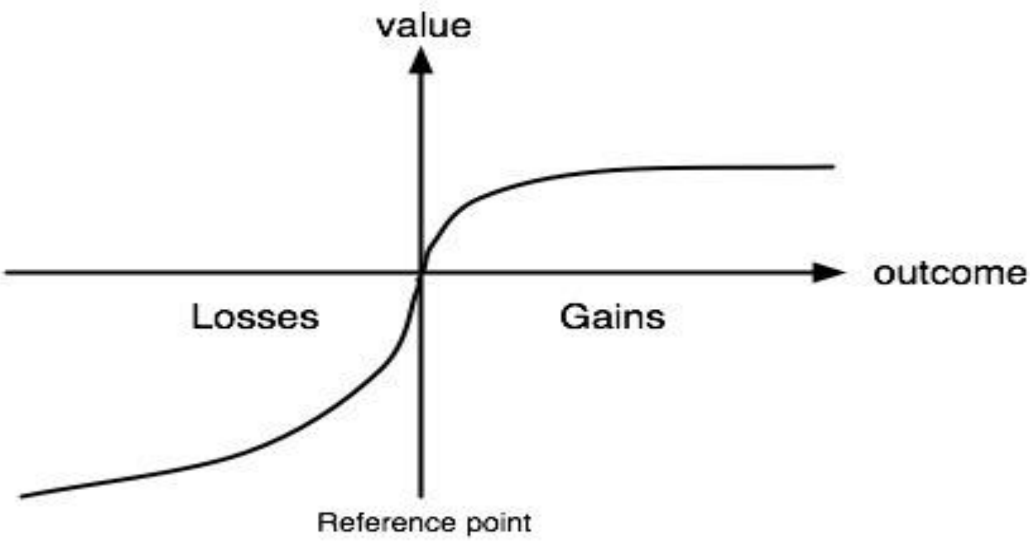
It is this overconfidence and failure to acknowledge their informational shortcomings that Shefrin (2000) believes results in poor investment decisions. Overconfidence coupled with self-attribution bias causes investors to trade too aggressively and may contribute to momentum (Kyle and Wang, 1997; Gervais and Odean, 2001).

Moreover, Shefrin (2000) finds that overconfidence amongst investors explains at least part of the PEAD. Shiller (2000) and Shefrin (2000) note that investors are overconfident and this in turn results in more frequent trading. Similarly, Barber and Odean (1999) report that overconfidence increases trading volume and hence overconfident investors sell winner stocks too early and hold onto losing stocks too long, this is referred to as the disposition effect.

2.5.4 Prospect theory and the disposition effect

An alternative to expected utility theory for decision-making under risk is prospect theory. This theory can be used to explain momentum in markets. Prospect theory describes various mental states of individuals and proposes that individuals overweight outcomes considered certain. Rather than evaluating the outcome in terms of the overall level of wealth, individuals evaluate gains and losses, with mental accounting referring to how decisions are evaluated over time. Central to prospect theory is loss aversion; Loss aversion refers essentially to investors being risk averse if experiencing gains and risk seeking if incurring losses. Tvede (1999, p. 94) in *the Psychology of Finance*, aptly described prospect theory as being ‘less willing to gamble profits than loses’. Figure 2.3 below diagrammatically represents prospect theory.

Figure 2.3 Prospect theory



Source: Kahneman and Tversky (1979)

An implication of prospect theory is the disposition effect, referring to an investor's tendency to sell stocks prematurely to secure gains and hold losing stocks for longer in the hope of recovering the loss and avoid the potential pain of realising the loss (Shefrin and Statman, 1985). The avoidance of realising losses and the hastily selling of winning stocks results in underreaction to news. Frazzini (2006) notes that underreaction is not limited to bad news, as good news is often assimilated slowly throughout the market also.

Pasquariello (2004, p. 277) notes that 'recent work employs modified versions of prospect theory to interpret the behaviour of financial investors and study the pricing of financial securities'. Campos-Vazquez and Cuilty (2014) also argue that the most appropriate measure of decision-making under uncertainty is prospect theory; additionally they posit that risk averseness is increased in the gain domain; these results are consistent with the work of Heilman *et al.* (2012) and Treffers *et al.* (2012).

Grinblatt and Han (2005) make a connection between prospect theory and momentum, affirming that prospect theory and mental accounting create a spread between equilibrium stock market value and a stock's recent capital gains relative to some reference point like a 52-week price maxima, resulting in momentum. Furthermore, momentum traders are not as sophisticated and slightly less risk averse than other traders (Menkhoff, 2010). In an investigation of momentum in the Australian market, Phua *et al.* (2010) show that the disposition effect is the best model to explain the observed momentum returns in their study.

2.5.5 Anchoring, availability and representativeness

Daniel Kahneman and Amos Tversky are key contributors to the literature on the incorporation of psychology and human behaviour to explain investors' decisions. Kahneman and Tversky (1974) discuss the theory of heuristics and biases which centre on the beliefs and preferences of individuals and how future expectations are formed. Anchoring refers to an investor's tendency to anchor expectations around a certain reference point and place too much weight on certain information, failing to adjust fully from this reference point. The reference point may be either accurate or significantly inaccurate. Anchoring is particularly relevant in financial markets as information is often difficult to obtain and process (Mussweiler and Schneller, 2003), leading investors to make judgements while failing to adjust for new information.

Another heuristic or rule of thumb that investors often employ when making decisions is availability. Availability refers to the ease at which a past occurrence of a similar event can be recalled by the investor, which may significantly affect future expectations. Both anchoring and availability may be heavily influenced by media coverage, as a particular event might receive ongoing attention, distorting the true significance of the event.

The representativeness heuristic refers to the similarity between the sample observed and the overall population; it refers to the level of similarities and characteristics shared by the sample population and the overall population from which the sample was taken. A decision or judgement is often made based upon how likely the sample corresponds to, and is a true representation of, the overall population. Representativeness entails estimation and assessment based on stereotypical assumptions; however it may be a result of sample-size neglect or base-rate neglect (Kahneman and Tversky, 1974). Base-rate neglect refers to a tendency to overweight recent information without acknowledging the impact of this new information on the original assumptions. Sample-size neglect results from a failure to acknowledge the level of variance that may be present in a sample, resulting in a poor decision based on incomplete information.

The representativeness heuristic is particularly important as investors view analysts' recommendations and forecasts. It is unpractical to view every analyst's recommendation or forecast of a given stock, therefore a selection of recommendations and forecasts are viewed and a decision made based upon this sample. However, the accuracy of the decision is constrained by lack of knowledge of how the observed sample of analysts output fully reflects the entire population of analyst output.

Anchoring, availability and representativeness induce underreaction to new information and create a spread between a stock's fundamental value and its equilibrium price, thus inducing momentum in stocks prices or as Grinblatt and Han (2004) posit, creating a 'predictable equilibrium' interpreted as momentum.

2.5.6 Law of small numbers (LSN)

Developed by Tversky and Kahneman (1971) and later by Rabin (2002), the LSN is derived from the representativeness heuristic and implies that a small sample drawn from an overall population will resemble the overall population in all essential characteristics. A believer in LSN overestimates (over-infers) the power of the small sample and is overly confident of early trends observed in samples (Tversky and Kahneman, 1971). Similar to the law of large numbers, believers in the LSN assume that the sample viewed is an accurate estimation of the parent population. The over-inference from short sequences embedded in long sequences is attributed to the belief in the LSN (Kahneman and Tversky, 1981). This over-inference in the LSN leads to the creation of two fallacies; the gambler's and hot-hand fallacies.

The gambler's fallacy believer holds that a sequence of events must change, whereas the hot-hand fallacy believer insists that the same pattern of chance results will continue; i.e. there will be a streak. Shefrin (2002) states that gambler's and hot-hand fallacies are phenomena that are a result of an individual's observation of a sequence in a series of random events, or a result of individuals making predictions about future random events based on outcomes of previous random events (Oppenheimer and Monin, 2009). The fallacies arise as a result of the underestimation of the quantity of observations necessary to accurately represent the overall population from which the observations are drawn and the resulting belief that deviations in one direction will be corrected by deviations in the other direction.

Gilovich *et al.* (1985) illustrate a good example of the LSN in action. The authors collect a season of basketball data and determine if trends in shooting streaks could be identified. They document that statistical tests do not identify patterns and there is no existence of the hot-hand hypothesis in that season of basketball; however, individuals are led to believe in patterns or sequences in totally random events. Gilovich *et al.* (1985, p.311) outlines how individuals depart from the theory of randomness;

> People "see" a positive serial correlation in independent sequences, and they fail to detect a negative serial correlation in alternating sequences. Hence, people not only perceive random sequences as positively correlated, they also perceive negatively correlated sequences as random. These phenomena are very much in evidence even when the sequences are displayed to the subject rather than retrieved from memory.

A major implication of the LSN is an investor's tendency to make inferences about the discrete signals that they observe (Rabin, 2002). Investors' inferences may induce several trends in stock markets as investors' trade based on their inferences regardless of how the sample they observed truly reflects the overall population.

The hot-hand fallacy can also be associated with analysts and mutual fund managers, with a belief that managers who have done well in the past will continue to do so. Prior research finds evidence of continued good performance of mutual fund managers as Grinblatt and Titman (1989b) report significant evidence of persistence in mutual-fund returns. Conversely, Hendricks *et al.* (1993) find little evidence that superior funds have sustained success but rather identify an 'icy-hands' theory that the fund which has performed poorly in the previous 12 months will continue to underperform in the short-term. Furthermore, the funds are 'more inferior than hot hands are superior' (Hendricks *et al.* 1993, p. 122).

The hot-hand fallacy can also be used to describe momentum within markets, as momentum strategies involve buying stocks that have previously performed well and selling stocks that have performed poorly, i.e. stocks which have previously performed well (poorly) will continue to do so. Such is the importance of momentum that Carhart (1997) extended Fama-French's three factor model to include a fourth component; momentum. Carhart (1997) believes that mutual fund managers trading in stocks with previous good performance does not necessarily imply the mutual fund manager is skilled at picking stocks, but rather implies that the fund performed well by following a momentum strategy rather than stock picking ability.

The LSN has major implications for how investors view stock recommendations and earnings announcements as it is impractical to view all possible recommendations issued by analysts within a certain time frame; instead an investor observes a small sample of the overall population and makes an investment decision based upon the sample viewed.

Forbes and Igboekwu (2015) illustrate how the application of the LSN to earnings announcements affects monthly responses by applying two representative agent models (Rabin (2002) and Barberis *et al.* (1998)) on the S&P 500 constituents between 1991 and 2006 and document evidence of monthly earning responses to a sequence of quarterly earnings announcements. Forbes and Igboekwu (2015, p.475) further illustrate the importance of the decision environment, stating that an investor 'conditions his response to earnings announcements according to the state of the world they currently believe to hold'. This again relates to the fact that investors fail to adjust their views based on the information that they receive or in the context in which they receive the information.

2.5.7 Noise traders

Noise trading can take on many forms and is only destabilising when a high degree of correlation between similar noise trading strategies exists; an example of this would be when noise traders exhibit herding tendencies (Koutmos, 2014). One destabilising consequence of noise trading is positive feedback trading which is discussed in section 2.5.8.

Shleifer and Summers (1990) state two assumptions about market participants; firstly, all investors are not fully rational in financial behaviour and demand for assets is affected by sentiments and beliefs and decisions are not fully justified by fundamental news about future asset values; secondly, arbitrage. Shleifer and Summers (1990) along with De Long *et al.* (1990) and Shleifer and Vishny (1997) argue that prices may be influenced by the actions of noise traders even if the market includes some well informed investors, as the well informed investors are constrained by risks. Noise traders may engage with financial markets for perfectly rational reasons; however, they may be irrational in their financial market behaviour.

Black (1986) acknowledges the coexistence of both the ‘informed’ trader and the ‘noise’ trader, stating ‘the price of a stock reflects both information that information traders trade on and the noise that noise traders trade on’ (Black, 1986, p. 532). Black (1986) further states that informed traders do not eliminate the effect of noise traders on stock prices, as even if their information may be valuable a profit is not guaranteed, so ‘noise traders create their own space’. Black (1986) also states that a level of ambiguity exists between who is an information trader and who is the noise trader. De Long *et al.* (1990) report that an inability to identify the trades of noise traders, result in the risk-averse rational investor avoiding noise prone stocks.

De Long *et al.* (1990) determine that noise trading can create a divergence between fundamental values and market prices as long as arbitragers have short horizons, fearing to offset noise traders activity because mis-pricing may be even worse in the next time-period. Furthermore, noise traders may be rewarded for bearing the risk they create and those returns may exceed those on offer to an information trader. Similarly, Hirshleifer *et al.* (2006) observes that irrational investors can earn abnormal returns in certain circumstances. Hence noise-trading can be self-sustaining.

2.5.8 Positive feedback trading

A consequence of noise traders is positive feedback trading and refers to ‘trend chasing’. Positive feedback traders are those that buy stocks when prices rise and sell stocks when prices fall (De Long *et al.* 1990). Positive feedback trading destabilises prices further from their true fundamental value, as rational investors who receives good news today buy more today, knowing that the increase in price will induce positive feedback trading tomorrow and drive prices further from their fundamental value (De Long *et al.* 1990).

Shiller (1989) alludes to the evidence that many individual investors trade for the first time following major bull markets, trading on the basis that stock markets are on the rise. Koutmos (2014) documents evidence of positive feedback trading in stock indices, index futures, and foreign exchange markets.

Bange (2000) uses survey data between 1987 and 1994 to investigate shifts in stock market forecasts and portfolio allocation decisions. Bange (2000) finds that shifts in portfolios are a reflection of past market movements, consistent with positive feedback trading. Furthermore, Bange (2000) finds that individual US investors increase their stock holding when S&P 500 returns are unexpectedly high. Kaniel *et al.* (2008) note an increase in selling by individual investors on the NYSE following price increases.

Shi *et al.* (2012) study the presence of day-to-day positive feedback trading in US stocks between 1980 and 2009 over six month trading periods and finds evidence that positive feedback trading is stronger following stock price increases. Moreover, Shi *et al.* (2012) observe that the degree of information uncertainty affects the level of positive feedback trading within certain stocks. Specifically, Shi *et al.* (2012) reports that positive feedback trading is intensified in stocks which have a higher degree of information uncertainty associated with them. This finding is consistent with the model of Hong and Stein (1999) and proposes that positive feedback trading contributes to momentum as momentum traders react to the trading of news watchers. Similarly, Shu (2009) observes that momentum is more pronounced in stocks with a larger number of positive feedback trading institutions.

Xiong and Ibbotson (2013) document that accelerated growth and investors' excitement are common characteristics prior to market crashes; this pre-crash acceleration may be a result of positive feedback trading, this presages the subsequent crash as the increasing price is not sustainable.

2.6 Industry momentum

A seminal paper by Moskowitz and Grinblatt (1999) examining industry momentum in the US market between 1963 and 1995 finds that industry momentum is the driving force of individual stock momentum, with industry momentum most profitable in the short-run, specifically a one-month horizon. Additionally, Moskowitz and Grinblatt (1999) assert that industry momentum is robust for various specification modifications; however, they do not conclusively discover the main cause for industry momentum but speculate that both rational and behavioural explanations are plausible. Pan *et al.* (2004) find evidence in support of Moskowitz and Grinblatt's (1999) findings, and further suggest that industry momentum is driven by auto-correlations across an industry. Lo and MacKinlay (1990) report similar findings, that the returns of large stocks lead those of smaller stocks.

Fraulo and Nguyen (2009) find that industry momentum strategies are more profitable than individual momentum strategies in the S&P index across 69 industries between 1998 and 2001, but in the slightly longer time horizon of six months. Shynkevich (2013) finds evidence of industry momentum in a study of the NYSE, AMEX and NASDAQ between 1991 and 2011. Similarly, Chordia and Shivakumar (2002) report a monthly return of 0.58 per cent for industry momentum in the US.

Campbell et al. (2001) report that between 1962 and 1997 individual firm level volatility increased noticeably more than market volatility, suggesting that a well-diversified portfolio across industries may be more stable and profitable that individual stock portfolios. The differential between industries may be due to the differences in the rate of information diffusion throughout the industries; Moskowitz and Grinblatt (1999), Hou (2001) and Lee and Swaminathan (2000) document that industries with a relatively low rate of information diffusion tend to have more prominent momentum.

Furthermore, momentum strategies may contain a style component relating to their industry classification and this may impact upon the level of momentum observed (Chen, 2003). Likewise, Safieddine and Sonti (2007) postulate that individual stock momentum is dependent on industry growth and firms in higher growth industries have greater individual stock momentum. Giannikos and Ji (2007) and Grundy and Martin (2001) assert that individual and industry momentum are separate effects.

Giannikos and Ji (2007) study industry momentum across 37 countries and report that with a one-month lag between ranking and holding periods, with a 6/6 strategy and returns aggregated across regions, industry momentum is profitable. Swinkles (2002) investigates momentum in the US, Japan and across Europe between 1973 and 2000 using 40 Datastream industry classifications; and report industry momentum in the US and across Europe is profitable using a skip-a-month 6/12 industry momentum strategy. Novy-Marx (2012) reports that industries exhibit momentum in very short horizons and is largely driven by intra-industry lead lag effects.

Su (2011) observes evidence of industry momentum in the Chinese stock market between 1994 and 2008, classifying stocks into industries using a single-digit *SIC.* Herberger *et al.* (2011) report momentum in the Swiss stock market between 1979 and 2009 is driven primarily by the performance of stocks in the high-technology industry, with high-technology industry generating monthly returns of 1.82 per cent.

Thomas and Zhang (2008) investigate the impact that earnings releases from early announcers have on the earnings releases of late announcers within industries; and find that momentum in industries is created as the stock market overreacts to the intra-industry implications of the earlier announcers and only corrects upon the late announcers' disclosure of earnings.

2.7 Momentum trading by analysts

The professionals within the market play an important role in forming market prices, as not only do institutions control a large number of trades but individual investors are heavily influenced by their actions. A full discussion on the behaviour of brokers and analysts is presented in chapter three.

Analysts themselves may engage in momentum trading for a number of reasons. Bange and Miller (2004) report that analysts tend to recommend stocks that previously performed well (momentum trading) and that this momentum induces further momentum as investors react to the recommendation. Desai *et al.* (2008) present evidence of analysts following momentum strategies. Additional evidence of momentum trading by analysts is contained in chapter three, section 3.7.

2.8 Reversal

A plethora of literature is available on the presence of momentum in international markets; the consensus is that momentum is an international stock market phenomenon. A brief discussion on the rigorous debate of the causes of momentum was detailed in earlier sections ranging from rational explanations to behavioural models to explain investor behaviour. The consensus of prior literature is that momentum is present in markets in the short to medium term but does momentum remain profitable in the long term?

De Bondt and Thaler (1985) infer that profits generated as a result of momentum trading are only present for a one-year time period and reversal occurs in the long run, suggesting that uniformed investors are at least in part responsible for long-term price reversals. Studying changes in fundamental particulars (earnings, cash flows and profit margins) of the company before and after momentum sorting, Chen *et al.* (2009) conclude that winner stocks experience more positive shocks to fundamentals than loser stocks. However, nine months after momentum sorting the winner stocks experience less positive shocks than loser stocks, hence winner stocks show evidence of reversal.

Bhojraj and Swaminathan (2006) report evidence of momentum in international stock markets reversing in the two years' post portfolio formation. Similarly, Hu and Chen (2011) find evidence of momentum reversing after one year for long ranking periods and after two years for short ranking periods. Jegadeesh and Titman (1993) find that after the first year, partial reversal of returns is present for the following two years.

Although, proponents of momentum in the short to medium term, Jegadeesh and Titman (2001) argue that momentum reversal is evident in the long run, therefore challenging the more rational explanations of momentum. Similarly, Conrad and Yavuz (2011) posit that momentum patterns are evident in intermediate time frames, but reversals begin to occur for all investment portfolios over longer time periods.

Yi-Yu (2011) finds that in the long-term reversals are sequential components of how the market absorbs and reacts to news; therefore momentum is a short-term phenomenon. Momentum trading often occurs in response to significant changes in price level over longer time periods of price observations rather than as a result of the last increase in stock prices. This infers that momentum trading is stronger as price change continues. Chan (2003) compares the monthly returns of stocks with identifiable public news and stocks with similar returns but no identifiable public news. Chan (2003) reports a significant difference between the two sets of stocks and further documents evidence of reversal in prices when initial price movement is unaccompanied by public news.

Applying the behavioural model of Hong and Stein (1999), Bloomfield *et al.* (2009) postulate that although short-term momentum remains a feature of financial markets, it is probable that in the long-term reversal will occur as the markets undo the initial overreaction suggested by their model. Particularly when markets contain a high proportion of traders who are willing to trade based on price movements. Hu and Chen (2011) report that momentum profits decrease gradually after a period of nine months.

Unlike reversal, which signals a change in the opposite direction, mean reversion refers to the stock price eventually returning to its mean or average value. Forbes (1996) argues that mean reversion and reversal are inextricably linked phenomena, as it would be almost impossible to identify mean reversion without identifying trends of reversal. Balvers *et al.* (2000, p. 746) also allude to the difficulty in isolating the presence of mean reversion in stock prices, stating; ‘mean reversion, if it exists, is thought to be slow and can only be picked up over long horizons’.

Fama and French (1988) and Poterba and Summers (1998) find evidence of mean reversion in US stock prices. Lo and McKinlay (1988) provide conflicting evidence of mean reversion in stock prices. Kim *et al.* (1991) tests the presence of mean reversion pre- and post- World War II and finds that it is a pre-WWII occurrence.

Balvers *et al.* (2000) postulate that mean reversion and momentum can occur simultaneously in the same set of assets, in a study of 18 developed countries. Similarly, Huang *et al.* (2013) demonstrate mean reversion and momentum co-existing in the S&P 500 index.

2.9 Chapter summary

This chapter introduced the momentum anomaly and a momentum trading strategy as well as presenting the evidence on the presence of momentum in international markets. Overall the evidence pertains to momentum being a persistent anomaly in stock markets internationally. Furthermore, evidence on the presence and performance of industry momentum is presented.

Prior literature debates the main causes of the anomaly, including a contentious debate between rational and behavioural explanations. Rational explanations include macroeconomic, market volatility, business cycles, transaction costs, liquidity risk and firm-specific characteristics.

The evidence suggests that behavioural explanations are a more appropriate explanation of momentum, these include; underreaction, conservatism bias, overconfidence, prospect theory and the disposition effect, along with noise traders and positive feedback trading. Prominent behavioural models include those developed by; Hong and Stein (1999), Barberis *et al.* (1998) and Daniel *et al.* (1998).

Evidence regarding the reversal of trends in momentum is also included in this chapter. The link between analysts and momentum is introduced with further evidence on the behaviour of analysts to follow in chapter three.

Chapter Three – Brokers and Analysts

3.1 Introduction

The role of brokers and analysts, the professionals in the market, is becoming increasingly significant in financial markets. Both institutional and individual investors rely heavily on the information that analysts provide (Jegadeesh *et al.,* 2006; Bird and Casavecchia, 2007). Analysts play an important role in gathering information, forming recommendations and forecasts and distributing this information to investors.

The impracticality of a single investor gathering all the necessary information to make an informed investment decision induces the need and reliance on analyst advice. Additionally, upon gathering this necessary information the investor may lack the required skills to process and disseminate all the relevant information, thus investors are willing to pay analysts for their services (Grossman and Stiglitz, 1980). Due to this reliance, analysts must provide adequate information to investors. However, analysts are human too and not immune to behavioural biases that affect investors, such as overconfidence, herding and underreaction. Furthermore, analysts face further challenges when processing information such as; their proximity to the underwriter of the stock and other numerous potential conflicts of interest that impact on analyst accuracy and the timeliness of announcements. There are numerous conflicts of interest that may affect analyst behaviour over time, which are discussed in later sections.

A core function of analysts in markets is to provide recommendations regarding a stock's expectations based on forecasted earnings and company fundamentals (Ivkovic and Jegadeesh, 2002; Cohen *et al.*, 2010). Keane and Runkle (1998) find earnings per share are constructed in an unbiased manner, however, De Bondt and Thaler (1990) caution that analysts are subject to the same bounded rationality as individual investors and behavioural biases can have long-term ramifications on a stock's true value (Malkiel *et al.,* 2009). Doukas *et al.* (2005) find that firms with significantly more analyst coverage tend to trade above their fundamental value, whereas firms with low analyst coverage trade below fundamental value.

Although the core function of an analyst is to issue unbiased recommendations and forecasts, conflicting motives for constructing that recommendation or forecast may exist. Forbes (2013) alludes to the dual function of an analyst; a research role and a role in incentivising trade and investment-banking activities. Understanding the behaviour of analysts is crucial in order to effectively determine the reasoning behind their recommendations and make informed trading decisions.

The remainder of this chapter discusses the potential trading value of analysts' recommendations and potential conflicts of interest that analysts face in constructing their forecasts and recommendations. The cognitive biases analysts are subjected to are also detailed, along with the process of how recommendations and forecasts are issued. Finally, the regulator's role in addressing the issues analysts face is also outlined.

3.2 Value of analysts' recommendations

Since the seminal study by Cowles (1933) investigating the role of professionals within the market a contentious debate surrounding whether recommendations have investment value has ignited. The value of analysts' recommendations can be determined by analysing the predictive power of their recommendations.

Historical evidence is conflicting as to the value of analysts' recommendations; Colker (1963) finds recommendations do not yield abnormal returns; similar evidence is cited by Diefenback (1972) and Logue and Tuttle (1973). Others find evidence that analysts' recommendations create investment value (Cheney, 1969; Groth *et al.*, 1979; Givoly and Lakionshok, 1979). Bidwell (1977) finds no evidence of investment value in a random sample of brokerage research reports for 1970 to 1973. However, in a study of Canadian brokerage houses recommendations, Bjerring *et al.* (1983) observe a positive relationship between future stock prices and analysts' recommendations. Elton *et al.* (1986) report excess returns within the month of recommendation issue in a study of 33 brokerage houses between 1981 and 1983. Lee (2000) affirms that analysts' recommendations have predictive power, but cautions that recommendations may contain an element of bias.

The strength of the recommendation may also affect the level of stock price impact; the more extreme the recommendation, i.e. strong sell (strong buy) as opposed to hold or sell (buy), the greater the effect on stock prices. Stickel (1995) reports that recommendation announcements result in a short-term price reaction and the level of reaction is dependent on the strength of the recommendation. Womack (1996) finds a similar significant price and volume response to the release of analysts' recommendations. Both Stickel (1995) and Womack (1996) report that a positive recommendation results in a positive return. Aitken *et al.* (2000) reach a similar conclusion, further stating that sell recommendations can have a more lasting effect on stock prices.

Jegadeesh and Kim (2006) find value present in analysts' recommendations in a study of G7 countries; US, UK, Canada, France, Germany, Japan with the notable exception of Italy. Additionally, value in analysts' recommendations is not confined to developed markets; Moshirian *et al.* (2009) report a significant stock-price reaction following the issuance of analysts' recommendations or revisions of recommendations in thirteen emerging markets from 1996 to 2005. Moshirian *et al.* (2009) go further to compare the stock-price reaction in developed and emerging markets and report a stronger positive reaction in emerging markets. Emerging markets are often more volatile and riskier; therefore, analyst research is of crucial importance in guiding investors (Bekaert *et al.*, 1997).

Since the seminal studies into the value of analysts' recommendations by Stickel (1995) and Womack (1996), the focus of many studies has shifted from investigating the impact of recommendations to investigating the impact of revisions in recommendations; suggesting that it may not be the original recommendation that induces the greatest stock price reaction but rather the change in recommendation. Jegadeesh *et al.* (2004) confirm this premise, observing that the greatest investment value can be found in the recommendation revision. Likewise, Womack (2006) and Green (2006) state that the change in recommendation level encapsulates the greatest investment value and that by paying particular attention to the change/revision in recommendation, excess returns can be achieved. Conrad *et al.* (2006) affirm that analysts' revised recommendations to major company announcements are incorporated into large price movements.

Ryan and Taffler (2006) examine the UK market between December 1993 and June 1995 and find that recommendation revisions have a significant impact on share prices. The stock price is found to react at the time of recommendation revision as well as the subsequent months following the revision, demonstrating that recommendations revisions contain investment value.

Givoly and Lakonishok (1979) document evidence of forecast revisions providing investment value to investors.

Stock price increases also occur prior to recommendation issue date; Aitken *et al.* (2000) observes returns in the pre-announcement period being higher, implying analysts may be reactive rather than proactive. Similarly, Groth *et al.* (1979) observe the level of returns pre-issue exceed those in the post-issue period. Evidence of momentum trading by analysts is detailed in section 3.7.

3.3 Conflicts of interest

Much of the argument regarding the value of analysts' recommendations centres on the debate of whether analysts are free from bias or are the conflicts of interest that they face too great, resulting in inaccurate, biased recommendations and forecasts. A conflict of interest is a circumstance that arises when a party can be potentially better off by pursuing a course of action that would be detrimental to a third party (Mehran and Stulz, 2007).

Several studies report conflicts of interest including; Dugar and Nathan (1995), Lin and McNichols (1998), Michaely and Womack (1999) and Jegadeesh *et al.* (2004). However these authors posit that the market is aware of conflicts of interest and the market price acknowledges the potential presence of bias. The causes of biased recommendations and forecasts are manifold and these are discussed in the following sections.

3.3.1 Causes of conflicts of interest

The desire for analysts to produce unbiased accurate research is challenged by incentives to bias the research in some form to achieve an alternative objective. Some of the main theories put forward to explain the conflict of interests analysts' face include; an analyst's desire to maintain access to senior level management; the 'information hypothesis' (Francis and Philbrick, 1993). The pressure to construct favourable recommendations and forecasts in order to maintain or develop relationships with lucrative clients; 'bribery hypothesis' (Dugar and Nathan, 1995)

As stated previously, the dual role of an analyst to provide independent research and incentivise investment-banking business can result in bias (Forbes, 2011). Analysts must maintain access to high-level investment managers and maintain a good relationship with investment-banking clients in order to avail of privately-held information regarding a firm. Failure to do so may result in the isolation of an analyst from valuable firm information, in other words being 'shut-out' as it were. This need to maintain access to investment management is referred to as the 'information hypotheses'.

Research by Francis and Philbrick (1993) acknowledges the need for analysts to issue favourable research to maintain access to management. This finding is further supported by Lim (2001). Chan *et al.* (2003) also find that analysts are reluctant to issue negative recommendations to avoid antagonising firms and maintain access to investment managers. Hayes (1998) and Irvine (2004) state that bias in analysts' forecasts and recommendations may be present to generate institutional business.

Chan *et al.* (2003) find that during the bull market of the 1990s conflicts of interest were amplified by the boom in investment-banking activities and an incentive to adjust earnings forecasts in an attempt to avoid earnings disappointments. Similarly, Shiller (2000) reports that managers often attempt to boost stock prices by encouraging favourable analyst coverage. In a comprehensive study, Agrawal and Chen (2012) study in excess of 110,000 recommendations issued by more than 4,000 analysts between 1994 and 2003, from both public and private analyst employers. Using univarate tests and cross-sectional regressions, controlling for the size of analyst following, analyst experience, workloads, reputation and resources; they find that analysts respond to pressure from investment-banking activities. Agrawal and Chen (2012) also observe evidence to suggest that although an element of bias is found in recommendations and forecasts, investors are sufficiently knowledgeable to adjust for any potential conflict of interest or bias when making their investment decision. Conversely, So (2013) concludes that investors fail to fully reverse the predictable bias in analysts output.

The difference between affiliated[45] and unaffiliated analysts is also discussed in prior literature. Dubois and Dumoniter (2008) assert that motives for issuing recommendations may be compromised if an analyst is affiliated with the underwriting firm. Similarly, Dugar and Nathan (1995) and Michaely and Womack (1999) both report that affiliated analysts tend to be more optimistic in their forecasts when compared to unaffiliated analysts. However, Ryan and Taffler (2006) find that analysts with investment-bank affiliations do not have an adverse effect on returns associated with buy recommendations.

Barber *et al.* (2007) highlight potential differences between the value of affiliated and unaffiliated analysts' recommendations. Barber *et al.* (2007) observe in excess of 300,000 recommendations issued by 409 securities firms for over 11,000 companies and report that since the downturn of the early 2000 a significant difference is evident between the investment value offered by affiliated and independent analysts. Furthermore, the recommendation upgrades issued by affiliated analysts under-perform recommendation upgrades issued by unaffiliated analysts. This evidence suggests that affiliated analysts' recommendations may incorporate a significant level of bias due to conflicts of interest.

Cowen *et al.* (2006) postulate that, perhaps in an attempt to avoid earnings disappointment, analysts of affiliated firms issue less optimistic recommendations and forecasts. Jacob *et al.* (2003) report that earnings forecasts issued by affiliated analysts are more accurate in the short-term than those issued by unaffiliated analysts perhaps due in part to higher skill levels and availability of resources at investment banks.

---

[4] See Appendix A for a full review of studies on international momentum.

[5] Affiliated refers to an analyst who is employed by a firm that has investment activities and underwrites the securities of a firm.

Furthermore, Dechow *et al.* (2000), O'Brien *et al.* (2005) and Barber *et al.,* (2007) find that affiliated analysts are more optimistic in forming forecasts and exhibit a greater reluctance to downgrade stocks after negative news than their unaffiliated colleagues.

Differences are also apparent between the behaviour of sell-side and buy-side analysts, with buy-side analysts tending to be more optimistic in their recommendations than their sell-side colleagues. In a large investment firm during the period 1997 to 2004, sell-side analysts tended to be more pessimistic in their recommendations and earnings forecasts (Groysberg *et al.*, 2011). Other studies find that investment banks tend to more heavily influenced by the recommendations and earnings forecasts of their own analysts than of those affiliated with other investment banks (Frey and Herbst, 2014; Jordan *et al.*, 2012).

The bribery hypothesis refers to the implicit or explicit pressure on analysts to bias their recommendations and research to gain favour of current or potential clients and boost investment-banking revenues (Dugar and Nathan, 1995; Lin and McNichols, 1998). Kolasinski and Kothari (2004) ascertain that the 'bribery hypothesis' causes bias in analysts' forecasts and recommendations. Additionally, Kadan *et al.* (2009) also find evidence to support the suspicion that investments managers lean on analysts to issue positive recommendations and forecasts to avoid an embarrassing downgrade of a valued client.

Furthermore, Irvine (2005), Jackson (2005) and Cowen *et al.* (2006) postulate that favourable research stimulates trading and thus generates brokerage commissions; this is referred to as the 'underwriting hypotheses'. Jackson (2005, p. 673) states that an analyst

> faces a conflict between telling the truth to build her reputation versus misleading investors via optimistic forecasts to generate short-term increases in trading commissions.

Prior to the enforcement of policies and regulation relating to conflicts of interest, it was a widely-held belief that an analyst's reputation would reinforce the necessity for accurate, unbiased forecasts and recommendations. It is possible that the analyst's desire to maintain a good reputation among their peers and be viewed by investors as issuing reliable accurate recommendations and forecasts, reduces the likelihood of analysts succumbing to investment-banking pressures and other related conflicts of interest.

Ertimur *et al.* (2006) and Mikhail *et al.* (2006) affirm that analyst reputation is enough to reduce instances of biased recommendations and forecasts. As analyst reputation is of significance both personally to the analyst and the financial institution they work for, analysts would be reluctant to engage in any behaviour that would adversely affect their reputation (Fang and Yasuda, 2014; Ljungqvist *et al.*, 2006). This evidence would infer that an analyst would not knowingly issue recommendations or forecasts which are cultivated in the presence of investment-banking pressures or knowingly contain bias. However, it is possible that the private career concerns of the analyst may have to be sacrificed in order to generate revenues for the investment-banking side of the firm (Ljungqvist *et al.*, 2006). Jackson (2005) finds that long-term analyst concern over reputation mitigates opportunistic behaviour; similarly, Michel and Pandes (2012) note that upwardly biased recommendations may endanger the reputation of the analyst.

It is assumed that a consistently accurate analyst would develop and maintain a good reputation in the financial community; therefore a positive relationship between reputation and performance is likely. Stickel (1992) reports that analyst reputation is directly correlated to salary, hence the necessity to issue accurate information. Li and Xin (2009) use, entry into, and continued membership of, the *Institutional Investor* the *All American Research Team*[6] as a proxy for analyst reputation; those who appear on

[6] *All American Research Team* annually publishes a list of the most accurate (successful) analyst over the previous year. Analysts are divided into several categories, for example; industry classification.

the list for successive years are less likely to issue overly optimistic recommendations for fear of future disappointment and irreparable damage to their reputation. Those named on the list command a greater salary, suggesting that their recommendations are more accurately viewed (Cohen *et al.,* 2010). Reinforcing the view that reputation and accuracy are undeniably linked, Xu *et al.* (2013) note that ‘star’ analysts issue more accurate recommendations and earnings forecasts.

In a study of analyst consistency, Hilary and Hsu (2013) reach three main conclusions. First, they find that analysts are less inclined to be demoted the more consistent they are with their recommendations. Second, there is a tendency amongst analysts to deliver downward-biased forecasts to increase their consistency, possibly at the expense of accuracy. Third, in institutional investors’ presence, the benefits of consistency are increasing.

The social network, or circle, that analysts are part of also impacts on the accuracy of their recommendations, so they are judged by the company they keep; Cohen *et al.* (2010) find that analysts who use acquaintances and relations within their social circle to gather information can form more accurate recommendations. Additionally, analysts may overlook the short-term gains associated with end-of-year bonuses, which are often generated by issuing optimistic recommendations for affiliated companies; instead they choose to issue recommendations that will not adversely affect their reputation, which is their long-term asset (Fang and Yasuda, 2014).

Compensation structure can also influence the construction of analysts’ recommendations and forecasts. It is commonplace for a significant portion of the analyst’s compensation to be directly related to the investment-banking revenue generated by analysts (Michaely and Womack, 1999). Groysberg *et al.* (2011) find evidence consistent with the theory that analyst compensation is structured to reflect the analyst’s contribution to brokerage and investment-banking revenues. Also, Groysberg *et al.* (2011) note that analyst compensation is positively correlated with 'all-star' recognition, the size of the analyst's portfolio and whether the *Wall Street Journal* recognises them as a top stock picker. However, in contradiction to Groysberg *et al.* (2011), Hong and Kubik (2003) observe that one of the primary focuses of analyst compensation is the accuracy of earnings forecasts.

Kothari (2001) asserts that the analysts that help generate additional trading business for the investment-banking side of the business earn higher compensation *ceteris paribus*. Similarly, those who generate less investment-banking profits are associated with higher analyst turnover (Mikhail *et al.,* 1999). Moreover, research suggests that optimism in analysts' recommendations is largely due to economic incentives and based on a desire to attract investment-banking business (Ackert and Athanassakos, 1997; Colarusso, 2001; Opdyke, 2002).

3.4 Optimism

As seen in previous sections, the effects of investment-banking pressures and reputation generally manifest themselves in optimistic analyst output. The debate surrounding the level of optimism in analysts' output is ongoing. Cowles (1944) conducted a study of analysts' recommendations over a number of bear market years and finds almost four times more bullish recommendations than bear recommendations despite the market conditions. Nutt *et al.* (1999) report evidence consistent with the theory that analysts have optimistic reactions to new information.

Generally, the frequency of buy recommendations issued by analysts is viewed as a measure of optimism. Stickel (1995) and Womack (1996) both report that the numbers of buy recommendations outnumber sell recommendations in US data by ratios of 3.2:1 and 4.6:1 respectively. Similarly, Ho and Harris (1998) record a significantly higher ratio of buy to sell recommendations of 7.1:1, whilst Moshirian *et al.* (2009) report a significantly lower ratio of 1.4:1 for emerging markets; Jegadeesh *et al.* (2004) and Jegadeesh and Kim (2006) observe similar trends. Specifically, Jegadeesh and Kim (2006) report that sell recommendations account for less than five per cent of overall recommendations between 1985 and 1998 for US data, with the frequency of sell recommendations reducing further for the period 1993 to 2001, indicating an increase in optimism during the later years of the study.

Prior to the introduction of policy and regulation, the level of optimism within analysts' recommendations was increasing; Barber *et al.* (2006) report the percentage of buy recommendations accounting for 74 per cent of overall recommendations in US data by mid-2000. In comparison, sell recommendations only accounted for two per cent, with hold recommendations making up the remainder. The number of buy recommendations decreases post-2000, possibly due to a decrease in optimism during this market time or as a consequence of the introduction of NASD rule 2711[7]. After the introduction of rule 2711, Mokoaleli-Moketeli *et al.* (2009) document that the frequency of buy recommendations decreased. Kadan *et al.* (2009) also find less evidence of optimistic recommendations post-2003, attributed in part to increased regulatory rules.

Optimism in analyst research is not a characteristic unique to developed markets; Moshirian *et al.* (2009) find that emerging markets recommendations are more positively biased than those of developed markets, albeit in a less extreme manner. Chopra (1998) observe that in rapidly-growing economies optimism may decrease but in an economic downturn optimism increases.

The many reasons for analyst optimism originate in the bias and pressures that they face when constructing forecasts and recommendations. The information and bribery hypotheses discussed in previous sections can induce overly optimistic analyst output.

[7] Regulations regarding the formation of analysts' research and reports, restrictions on the level of analyst involvement with investment-banking activities and managers, introduced in the US in 2003.

Further to these, the ‘selection hypothesis’ is suggested as a cause of analyst optimism. The selection hypothesis refers to an analyst’s tendency to cover stocks for which they have favourable views (McNichols and O’Brien, 1997), and not selecting to cover stocks for which they have unfavourable news, thus avoiding issuing negative recommendations and forecasts.

Clayman and Schwartz (1994) also attribute optimism in analyst output to analyst tendencies to ‘fall in love with stocks’. Das *et al.* (2006) argue that analysts selectively choose the firms and IPOs (initial public offering) that they cover. Similarly, O’Brien (1997) postulates that analysts selectively choose firms for which they have the most favourable forecasts. In addition, Easterwood and Nutt (1999) suggest that financial analysts underreact to negative news and overreact to positive news and new information, leading to a tendency to be over optimistic in their recommendations. Incorporating IPO literature to determine optimism in analyst recommendations, Bradley *et al.* (2003) find that analysts initiate coverage following an IPO with a buy or strong buy (optimistic) recommendation.

Hribar and McInnis (2012) find that analyst forecast errors are correlated with investor sentiment; moreover, analysts’ forecasts and one-year-ahead earnings are more optimistic in periods of high investor sentiment. However, the authors also note that bias as a result of sentiment is less likely to appear in recommendations. O’Brien and Tian (2006) investigate the role that recommendations played during the Internet bubble of 1996 to 2000 and find that upon comparing analyst recommendations of Internet IPOs to a sample of recommendations based on non-Internet IPOs, analysts are more optimistic about Internet IPOs. As a result, this optimism contributes to the 1996 to 2000 Internet bubble. Liu and Song (2001) evaluated forecasts issued both before and after the Internet bubble and find that forecasts are optimistic pre-bubble. Furthermore, writing in the *Wall Street Journal*, Malkiel (2002) states that corrupt research and biased recommendations can contribute to a bubble in an economy.

Additionally, the ‘information hypothesis’, as outlined previously, impacts the level of optimism in analysts’ forecasts and recommendations. McNichols and O’Brien (1997), Lin and McNichols (1998), Dechow *et al.* (2000) and Hong and Kubik (2003) assert that optimistic forecasts and recommendations are issued by analysts in order to maintain and secure investment-banking connections.

O’Brien *et al.* (2005) find that on the occasion when analysts are pressured to make optimistic recommendations, those with private information issue more timely upgrades. Hence, analysts are less likely to issue an upgrade after a positive information shock as their original recommendations would have incorporated this via the private information at their disposal. Contrastingly, analysts are more likely to downgrade stocks upon receipt of negative information as it is more justified to do so and their recommendation will not be viewed as unjustly negative. Similar conclusions are reached by Conrad *et al.* (2006), who examine recommendation revisions after extreme positive and negative shocks.

3.5 Herding and cognitive biases

Analysts are subject to the same behavioural and cognitive biases as investors and market participants. Poteshman (2001) and Covel and Shumway (2005, cited in Galarotis, 2014) report that traders at the Chicago Board of Trade and Chicago Board Options Exchange are affected by behavioural biases even though it is assumed these ‘professionals’ are far more sophisticated than the average investor.

In order for an analyst to make a recommendation, vast amounts of information are gathered and processed and used to form a recommendation. Due to the nature of this task, analysts may show tendencies to follow the prevalent consensus so as not to damage their reputation, resulting in herd-like behaviour among analysts. It is also possible that analysts issue recommendations in line with the consensus of fellow analysts to avoid being the ‘odd one out’. The tendency of analysts to follow the crowd and issue recommendations similar to the consensus recommendation is more prevalent when the consensus recommendation is optimistic (Welch, 2000).

Welch (2000) reports that analysts are influenced by the consensus recommendations and often mimic the behaviour of one another; this herding behaviour can drive momentum in markets. Furthermore, in a more recent study, Lin *et al.* (2010) find evidence that analysts exhibit patterns of herding. Hong *et al.* (2000) posit that analyst herding is a result of ignoring privately-held information and over-inferring the public information available.

Jegadeesh and Kim (2010) document evidence to support the herding hypothesis. Olsen (1999) finds that analysts herd in up to 72 per cent of forecasts between 1985 and 1987. De Bondt and Forbes (1999) report similar findings of analyst herding patterns in the UK market between 1986 and 1997.

3.6 Analyst behaviour during financial crises

Financial crises can have a significant impact on the way investors behave in the market; their perception of risk and expected market returns often fluctuate. Hoffman *et al.* (2013) investigate individual investor perception of risk and stock market return from April 2008 to March 2009 and find that risk tolerance is reduced during the economic crisis, although risk tolerance did begin to recover towards the end of the sample period. Decreases in investor risk tolerance affects the way that investment decisions are made and a change in perception would be expected at the height of the financial crisis.

Malmendier and Nagel (2011) postulate that extreme economic events such as those experienced during the Great Depression in the 1930s can have an enduring effect on investors’ risk-taking perceptions. During an economic crisis the market experiences a number of shocks (Dzielinksi, 2011); as a result, investors’ willingness to take on risk is often diminished (Barberis, 2013).

The output of analysts during times of economic turmoil is all the more important to investors. Ang and Ma (2001) summarise that analysts failed to foresee fundamental weakness in companies prior to the Asian financial crisis; furthermore analysts did not adequately adjust their forecasts post-crash. Loh and Mian (2003) reach similar conclusions and find that analysts’ forecasts contain systematic biases during the Asian crisis period.

Hsu *et al.* (2013) find that firms are reluctant to enter the public market during a financial crisis and analysts tend to make optimistic predictions about the firm after the financial crisis. Similarly, Loh and Mian (2003) find that in times of economic crisis and uncertainty, analysts make optimistic predictions. Papaioannou *et al.* (2013) find that investment performance is pro-cyclical in times of economic downturn. Sidhu and Tan (2011) find similar evidence of poor analyst performance during the 2008 financial crisis for US and Australian companies. Similarly, Arand and Kerl (2012) report deterioration in analyst accuracy between October 2007 and March 2009, using analyst report data from *FactSet Research Systems,* but find investors’ response to analyst output becomes more persistent and timely. This evidence illustrates that perhaps analysts are weakest when investors rely on them most.

3.7 Momentum trading by analysts

Several prior studies allude to the ability of institutional investors to move prices, either directly or indirectly (Nofsinger and Sias, 1999; Sias *et al.*, 2001; Griffin *et al.*, 2003: Chiao *et al.* 2011). The trading behaviour of institutions is imperative due to the influential role of institutional investors in markets.

Prior studies document that analysts and institutions engage in momentum or positive feedback trading; Bange and Miller (2004) find that brokers and analysts issue recommendations for stocks that have previously performed well (momentum trading); Jegadeesh *et al.* (2004), Jegadeesh and Kim (2006) and Desai *et al.* (2000) find evidence consistent with analysts following momentum strategies in US data. Badrinath and Wahal (2002) observe that institutions engage in momentum trades when trading stocks for the first time. Sorescu and Subrahmanyam (2006) observe that a large percentage of abnormal returns can be explained by momentum trading.

Muslu and Xue (2013) report that following the introduction of increased regulation in the US in 2003, the likelihood of analysts' recommendations following past stock returns is reduced. Furthermore, Muslu and Xue (2013) note that analysts follow a momentum strategy when issuing recommendations if their conflicts of interests are high and they have a reduced ability to gather fundamental information. Overall, they find that recommendations issued by positive feedback trading contribute to existing price momentum and exacerbate short-term and long-term returns.

Li and Uddin (2011) gather data on 'neglected stocks'[8] and find that analysts create momentum within stocks before issuing recommendations. Jaffe and Mahoney (1995) show that investment newsletters and circulars tend to recommend trading in stocks that have previously performed well. Conversely, Altinkilic and Hansen (2009) document that analysts' recommendation revisions are largely information free, i.e. revisions follow a stock price reaction to corporate news or events. Altinkili and Hansen (2009, p.17) state 'the findings go against the long-standing view that recommendations are an important means by which analysts assimilate information into stocks prices.'

[8] Neglected stocks refer to stocks with little or no analyst coverage.

3.8 How are forecasts and recommendations issued?

As stated previously, there is evidence that analysts' recommendations' contain investment value and move markets. However, there is some debate surrounding the issue process of analysts' reports; therefore, regulation was introduced to regulate the publication of analysts' reports. Pre-regulation period, Dimson and Marsh (1984) document analysts' recommendations are most profitable in the days prior to public release; trades made in the period after public release of analysts' recommendations are not as profitable. Analysts are effectively rewarded with high trading volume by 'tipping' certain privileged clients prior to public release of recommendations; regulations are now in place to eliminate this practice.

Lepone *et al.* (2013) investigate trading activities during a 21-day period around the public release of recommendations between November 2004 and November 2006 in the Australian Securities Exchange (ASX). Results indicate evidence of 'tipping' among small and mid-capitalised stocks prior to announcement, with analysts executing large trading volumes prior to the public announcement of recommendations. They conclude that 'information leakage' occurs one day before downgraded recommendations are issued to the public. Similarly, Craig and Corkery (2009) and Lepone *et al.* (2012) find leakages provide the possibility for abnormal returns to be earned for both downgrades and upgrades over a four-week period.

Irvine *et al.* (2007) observe an increase in institutional trading volume in the days prior to the public announcement of analysts' recommendations, suggesting that 'tipping' has occurred. Since the Galleon case[9], Agapova and Madura (2013) and Chira and Madura (2013) report that information leakage is reduced in US markets. Similarly, Madura and Premti (2014) postulate that regulation significantly reduced the prevalence of

[9] Various Wall Street professionals were charged with insider trading in October 2009. Although, the Galleon case is not directly related to information leakage, the alleged crimes are similar to what would be charged if analysts engaged in 'tipping' activities.

information leakage in the US stock market. Heidle and Li (2005), Green (2006) and Kim *et al.* (1997) report an increase in trading prior to publication of analysts' recommendations. Christophe *et al.* (2010) also report an increase in shorting activity prior to the public release of analysts' downgrades.

Self-regulation by investment and brokerage houses is becoming more prevalent to eliminate the practice of 'tipping' certain clients prior to publication of recommendation; Smith and Grocer (2012) report that an analyst was reprimanded as a result of 'information leakage' during the initial public offering of Facebook.

3.9 Regulatory response

Due to ongoing issues surrounding increasing optimism in recommendations and scandals such as the Global Analyst Settlement and the Bernie Madoff crisis, the introduction of formal measures to stem the excessive optimism and bias in analyst output was of critical importance. Analysts were seen to have an excessive informational advantage; therefore formal regulatory measures were necessary. The regulatory response varied across countries but many of the underlying policy principles are common across countries. Prior to official regulation, the so-called 'Chinese walls'[10] were believed to be sufficient in reducing the likelihood of conflict of interests. However, more stringent policies and punishments were required.

3.9.1 Market abuse directive (MAD)

In 2003 the European parliament adopted the Market Abuse Directive (herein referred to as MAD). Regulations outlined in MAD include; forbidding the manipulation of data and information, ensuring that all persons responsible for reporting or preparing

[10] Chinese Walls refer to a barrier between investment-banking activities of a firm and research activities. Information should not pass between the departments and the departments are effectively viewed as two separate unaffiliated institutions.

information with regard to recommendations including; brokers, analysts and media outlets fulfil certain obligations to avoid conflicts of interest arising (Central Bank of Ireland, 2012). Furthermore, any potential conflict of interest must be disclosed to the relevant authorities and regulatory bodies, with every effort made by financial institutions to establish 'Chinese walls' between investment and research departments (Jacob *et al.,* 2003).

Within the lengthy, robust policy, several articles within the directive are focused on protecting investors from biased recommendations that emanate from affiliated analysts. One such condition is that those who prepare recommendations must disclose and distinguish the information formed from opinions and estimates, from the factual information. Moreover, the time period in which recommendations are constructed must be stated along with any possible change of opinion within this time period. The MAD also addressed the conflicted structure of how analysts' compensation is formed.

Since the adaption of regulation in the US and Europe several studies have focused on the effectiveness of such regulation. Kadan *et al.* (2009) find evidence that regulation in the US actually decreased the informativeness of recommendations. Others find no change or decrease in the accuracy of forecasts or recommendations (Bailey *et al.,* 2003; Heflin *et al.,* 2003; Agrawal *et al.*, 2006; Mohanram and Sunder, 2006).

Lin and Miao (2010) observe that post-regulation bias in affiliated recommendations decreases and some decrease in bias is also observed for unaffiliated recommendations. Bradley *et al.* (2012) find evidence that an analyst's potential conflict of interest is diminished after the introduction of regulation.

3.9.2 US regulation

Following the Global Analyst Settlement in 2003, regulation was implemented in an 'attempt to mitigate the interdependence between the research and the investment bank departments of US brokerage houses' (Kadan *et al;* 2009, p. 4189). Regulation Analyst

Certification, rule 2711 and rule NYSE 472 were introduced in Spring 2003. The new regulation eliminates investment department involvement in the preparation and publication of analyst output; states the proper manner to structure analyst compensation; restricts the personal trading of analysts; requires publication of the number of buy, sell and hold recommendations published by an analyst; and enforces the separation of investment-banking activities and research activities.

Barber *et al.* (2005) find that the percentage of buy recommendations increased during the 1996 to 2000 period and upon implementation of NASD rule 2711 in mid-2000 the level of buy recommendations declined. The aforementioned rule was an attempt by policy-makers to provide the public with information, so that investors could evaluate the quality of analysts' recommendations. There may be many reasons other than the introduction of the new policies to explain the decline in the level of buy recommendations issued by analysts, including the decline in economic conditions during the time period concerned (Barber *et al.,* 2005).

Cornett *et al.* (2007) find that investors' response to analysts' recommendations is significantly reduced post regulation introduction. However, Goff *et al.* (2008) find that investment value is still encapsulated in analysts' recommendations post regulation introduction. Similarly, Chen and Chen (2009), Kadan *et al.* (2009) and Barniv *et al.* (2009) observe that recommendations are more reliable since the introduction of regulation 2711 in the US. Jeurgens and Lindsay (2009) argue that following the introduction of regulation, analysts seek alternative ways to provide value to investment clients and the leakage of information prior to analysts' announcements may be a way of providing such value.

The need to increase and extend regulation is highlighted in the Attorney General of New York Eric T. Schneiderman's address to New York Law School in March 2014; he alludes to the increasing role that technology plays in markets and the dangers associated with potentially high-frequency trading. A monumental agreement with the world's leading asset manager, *BlackRock*, led to the end of systematically surveying analysts for their opinion prior to the publication of reports. Furthermore, the attorney general supports an idea floated by economists at the Chicago Business School to limit the potentially destabilising impact of high-frequency trading. It involves an end to continuous securities trading and introduces the practice of trading in batches at frequent intervals to ensure that price and not speed is the determining factor of trade.

The increasing role of technology and social media in markets ensures that regulation and polices must be routinely adapted to cater for any potential unfair advantages that may arise in the market.

3.10 Chapter Summary

Chapter three synthesises the literature and evidence in relation to the role of brokers and analysts in stock markets. The important role they play within markets is highlighted as is the investment value contained within their recommendations and forecasts.

The various conflicts of interests analysts may endure are detailed as is the subsequent impact of the conflict on the investment value of analysts' recommendations. Evidence pertaining to the level of optimism in analysts output is also presented. Analyst tendency to engage in herding behaviour and the cognitive biases analysts are influenced by is detailed.

Analyst behaviour during times of market and economic turmoil is documented and evidence of analysts engaging in momentum trading. Finally, the regulatory response of policy makers to the conflicts of interest facing analysts and the effect of implementation of the said regulation is established.

Chapter Four – Data and Methodology

4.1 Introduction

This chapter describes the data and methodology used to answer the principal research questions of the thesis. These questions include; does momentum exist in the UK stock market between 1995 and 2015 and is it more prevalent in certain years; such as in times of economic crises. Also addressed is the issue surrounding the behaviour of brokers and analysts throughout this period, with particular emphasis on their behaviour during times of economic crises. To address this issue the level of optimism in their recommendations as well as the accuracy of their recommendations will be investigated.

To this end, this chapter is outlined as follows; section 4.2 details the data used to answer the research questions and section 4.3 relates to the specific methodologies used in order to achieve the research objectives concerning momentum. Section 4.4 presents the methodologies pertaining to statistical significance and section 4.5 outlines how survivorship bias is avoided and how missing values are dealt with in this study. Section 4.6 delineates the methodological approach to answering the research questions relating to the accuracy of analysts. Finally, section 4.8 concludes with a chapter summary.

4.2 Data description

This section details the data collected and the resources and databases used to collect such data. Data consisting of monthly returns are gathered from the ThomsonONE online database for stocks listed on the FTSE100 index between 1995 and 2015. The sample is representative as the FTSE100 index is a benchmark for companies operating in the UK stock market, it allows for performance of peers in the same category to be compared. The year 1995 was chosen for the start of the study as it precedes any market uncertainty associated with the Internet bubble and the global financial crisis. Furthermore, selecting 1995 as the start point allows for a substantial time frame of analysis; 20 years.

Analyst recommendations are drawn from the Morningstar extracted data file. Historic broker recommendations for UK registered and listed companies and monthly prices are collected from London Share Price Database (LSPD). Analysts' forecasts data is drawn from the I/B/E/S historical database, including companies' actual earnings and their matching analysts' forecasts. The data consists of over 342,586 recommendations for 3,991 companies in the UK from 136 brokerage houses.

4.3 Strength-rule methodology

This section outlines the various methodologies adopted to answer the research questions relating to the momentum anomaly outlined previously. The relative strength-rule strategy of Jegadeesh and Titman (1993) is largely followed. Whereby, the stocks/industries are ranked based on their returns over the previous period of time. If stocks/industries fall within the top/bottom performance percentile of returns then they allocated to the appropriate winner/loser portfolio. The construction of portfolios is discussed further in section 4.3.2.

Natural logarithms of prices are used, which Corrado and Truong (2008) argue improve the test statistic specification compared to using arithmetic returns and as they are time additive and log returns more closely resemble a normal distribution[11]. Cumulative abnormal returns (CARs) are used to calculate returns of the strength-rule strategy. The return generating models are outlined in section 4.3.1. CARs employ the use of the natural logarithms of prices, which. R_{it} is determined using the equation below;

$$R_{it} = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{4.1}$$

Where:

R_{it} is the return on stock i at time t;

P_t is the price at time t;

P_{t-1} is the price at time t-$_1$.

4.3.1 Return-generating models

The market model and the Fama-French (1993) three-factor model (hereafter referred to as FF3F) are the two models used to calculate abnormal returns. The market model developed by Sharpe (1963) simplifies portfolio theory, assuming that the common factor between all securities is their relationship to the market rate of return. Pilbeam (1998, p. 177) state the 'security is sensitive to fluctuations in the market as a whole', i.e. the only factor determining the return on security i at time t is the return of the market at time t. Sharpe's (1963) market model is denoted by equation 4.2 below;

[11] Fama *et al.* (1969) found that arithmetic returns and logarithmic returns produced equivalent results in their event study.

$$R_{it} = \alpha_i + \beta_i(R_{mt}) + \varepsilon_{it} \qquad \textbf{(4.2)}$$

Where R_{it} is the expected rate of return on security at time t;

R_{mt} is the expected rate of return on the market at time t;

α_i is a constant factor that varies between securities;

β_i measure of systematic risk.

The error term (ε_{it}) is interpreted as the abnormal return. A major advantage to this model is that fewer variables are required for the market model (Pilbeam, 1998) compared to the more complex Capital Asset Pricing Model.

Developed by Sharpe (1964), Lintner (1965) and Black (1972), the Capital Asset Pricing Model (CAPM) attempts to explain the relationship between the return and risk of a security. The theory behind the CAPM implies returns on a financial asset increase with risk. The CAPM is denoted by equation 4.3 below;

$$R_{it} = R_f + \beta_i\left(R_{mt} - R_f\right) + \varepsilon_{it} \qquad \textbf{(4.3)}$$

Where:

R_{it} is the expected return on the security at time *t;*

R_f is the rate of return on a risk-free asset at time *t;*

R_{mt} is the expected return on the market;

β_i measure of systematic risk;

ε_{it} is error term.

Extending the CAPM further, Fama and French (1993) develop a more rounded model to generate market returns to eliminate some of the criticisms levelled at the CAPM because of its underlying assumptions. Fama and French's (1993) three-factor model (FF3F) adds two additional variables to the CAPM to better explain return variations. These two additional variables account for the size and value premium. Fama and French (1996, p. 56) argue that the FF3F 'captures much of the variation in the cross-section of average stock returns, and it absorbs most of the anomalies that plague the CAPM'. Fama and French (1996) also assert that the FF3F does not explain the short-term continuation in returns as documented in Jegadeesh and Titman (1993). For this reason the FF3F model is selected, as it is deemed the most appropriate measure of returns for the strength-rule strategy[12]. Equation 4.4 below denotes FF3F;

$$R_{it} - R_{ft} = \alpha_i + \beta_i\left(R_{mt} - R_{ft}\right) + s_i(SMB_t) + h_i(HML_t) + \varepsilon_{it} \qquad \textbf{(4.4)}$$

Where:

R_{it} is the return on *i* at time *t;*

R_{mt} denotes the return on the broad market at time *t;*

R_{ft} is the risk-free rate of return at time *t;*

SMB_t (small minus big) denotes the size premium;

HML_t (high minus low) denotes the value premium.

[12] Hon and Tonks (2003) and Liu *et al.* (1999) use the Fama-French Three Factor model to measure returns.

The UK Fama-French factors are taken from the work of Gregory *et al.* (2013)[13], where R_m is the total return on the FT All Share Index and R_f is the monthly return on three-month UK Treasury bills.

4.3.2 Portfolio formation

A period of 20 years is selected to consider the profitability of the strength-rule strategy (momentum) in the UK stock market. The years 1995 to 2015 are chosen as 1995 precedes the financial turmoil of the Internet bubble and allows for the study of 20 years of financial data.

At time *t*, stocks are ranked based on their returns during the previous *J* months (3, 6, 9, 12 and 18 months). Equally-weighted[14] portfolios are then formed based on the stock's performance over the previous *J* months. 'Winner' portfolios consist of the top ten performing stocks during the rank period (*J* months). The bottom ten performing stocks then form the 'loser' portfolio. These equally-weighted portfolios are then held for a period of *K* months (hold period, 3, 6, 9, 12, 18 and 24 months).

Non-overlapping rank periods are used as Siganos (2010) states that the non-overlapping momentum strategies reduce trading frequency, thus minimising transaction costs as no monthly rebalancing of portfolios is required. Furthermore, non-overlapping time periods improves statistical testing. A self-financing investment strategy is assumed and average abnormal returns of the winner and loser portfolios are calculated for the following *K* months. The returns of portfolios are determined by the cumulative abnormal return (CAR). Testing the strength-rule strategy, momentum is present if $ACAR_W – ACAR_L > 0$. Where CAR_{pt} for *n* stocks at time *t* is calculated by;

[13] Gregory *et al.* (2013) factors underlying this study can be found at http://business-school.exeter.ac.uk/research/areas/centres/xfi/research/famafrench/

[14] Jegadeesh and Titman, (1993; 2001); Rouwenhorst, (1999); Moskowitz and Grinblatt, (1999) form equally weighted portfolios.

$$CAR_{pt} = \frac{1}{N}\sum_{t=1}^{T}\sum_{i=1}^{n}\varepsilon_{it} \quad \textbf{(4.5)}$$

As in Jegadeesh and Titman (1993), a second rank and hold strategy is adopted; whereby, a month is skipped between the rank and hold periods[15]. A month is skipped between rank and hold periods to avoid any bias associated with infrequent trading and bid-ask spread bias. Galariotios *et al*. (2007) and Jegadeesh and Titman (1993) posit that failure to skip a month between the rank and holding periods may fail to mitigate for such biases, resulting in profits being overstated. Jegadeesh (1990) further asserts that skipping a month between formation and hold periods eliminates short-term reversals.

The Sharpe ratio winner and loser portfolios are also calculated to measure the risk of the portfolio. Sharpe (1994) states that the 'Sharpe ratio is designed to measure the expected return per unit of risk for a zero investment strategy'. Generally speaking the higher the portfolios Sharpe ratio the better.

4.3.3 Strength-rule strategy and industry returns

The profitability of the strength-rule strategy in relation to industry returns is also tested. Moskowitz and Grinblatt (1999) derive strength-rule strategy returns for industries and their method is largely followed in this study. Stocks within the selected

[15] Jegadeesh (1990), Moskowitz and Grinblatt (1999), Swinkles (2002), Scowcroft and Sefton (2004) and Chu and Chiang (2010) all employ a strategy option whereby a month is skipped between formation and hold periods.

time frame of study are allocated to the most appropriate industry classification based on the two-digit[16] Standard Industry Classification code (SIC).

Table 4.1 Industry classification

This table details the number of companies allocated to each industry based on their relevant two-digit Standard Industry Classification code (*SIC*).

Industry	SIC Codes	Max Number of stocks
Agriculture, Forestry, Fishing	01-09	1
Mining	10-14	20
Construction	15-17	2
Manufacturing	20-39	63
Transportation and Public Utilities	40-49	35
Wholesale trade	50-51	3
Retail trade	52-59	17
Finance, Insurance, Real Estate	60-67	43
Services	70-89	25

Similar to the analysis of the individual strength-rule strategy, average industry returns are then calculated for each rank period. With a total number of nine industry classifications, the 'winner' portfolio consists of the top three performing industries;

[16] Moskowitz and Grinblatt (1999) form industry groups based on two-digit SIC codes.

and the ‘loser’ portfolio is made up of the bottom three performing industries during the given rank periods. Cumulative average abnormal industry returns are then calculated for the given hold periods. The rank periods remain 3, 6, 9, 12, and 18 months and the hold periods 3, 6, 9, 12, 18 and 24 months. It can then be determined if there is a significant difference between instances where the portfolios are formed on the basis of individual stock performance or alternatively on the basis of overall average industry performance[17].

4.3.4 Sub-sample time period analysis

Certain periods of time within the overall time-frame of study are isolated to determine if particular economic events impact on the presence and profitability of momentum in the UK stock market.

The Internet bubble years are isolated between 1995 through to 2002, to determine the effect on profitability of the momentum strategy pre-dot.com crash in April 2000 and subsequently post April 2000. Demers and Lev (2001) report that the value of Internet stocks plummeted by 45 per cent in the spring of 2000; their findings further suggest that Internet stocks were over-valued prior to the stock market correction in April 2000. The global financial crisis years are isolated to include the crisis at Northern Rock in September 2007 triggering the first UK bank-run in 150 years, coupled with destabilised markets and economic uncertainty, compounded internationally by the collapse of Lehman Brothers twelve months later in September 2008. Therefore, to allow analysis of these events on the profitability of momentum in the UK stock market the years 2005 to 2012 are isolated[18].

---

[17] For the purposes of explanation, from herein, individual momentum refers to portfolios formed on the basis of individual stock performance grouped in a portfolio, and industry momentum refers to portfolios formed on the basis of overall industry groupings.

[18] 2005 marked the onset of the bubble psychology of the global financial crisis period. The ending period of 2012 allowed for inclusion of any effect of EU wide changes to financial policy (Greek bailout agreement of February 2012).

The rank periods begin in the first month of the selected sub-periods and the hold period ending in the last month of the selected sub-periods. Analysis of sub-periods adds robustness, as it tests whether abnormal returns are attributable to the performance of the strength-rule strategy in a particular time period; as is highlighted by Hon and Tonks (2003), who find momentum in the overall time period is attributable largely to the performance of momentum strategies in the earlier years of their study.

4.4 Statistical significance

The abnormal returns of the strength-rule strategy are tested for statistical significance following the method outlined by De Bondt and Thaler (1985). The pooled estimate of population variance in CAR_t is donoted by $2S_t^2$;

$$2S_t^2 = \frac{\left[\sum_{n=1}^{N}(CAR_{wt} - AR_{wt})^2 + \sum_{n=1}^{N}(CAR_{Lt} - AR_{Lt})^2\right]}{2(N-1)} \qquad \textbf{(4.6)}$$

Where, CAR_{wt} and CAR_{Lt} are the cumulative average abnormal returns of winners and losers at time *t* and AR_{wt} and AR_{Lt} are the average returns of winners and losers at time *t* respectively. Assuming sample size *N* is equal for winners and losers the T statistic (T_t) is calculated by equation 4.7 below;

$$T_t = [ACAR_{Wt} - ACAR_{Lt}] \,/ \sqrt{\frac{2S_t^2}{N}} \qquad \textbf{(4.7)}$$

To test if $ACAR_{wt}$ and $ACAR_{Lt}$ are statistically different from zero the standard deviation of the winner portfolio is calculated by;

$$S_t = \sqrt{\sum_{n=1}^{N}(AR_{wnt} - AR_{wt})^2}\,/N - 1 \quad \textbf{(4.8)}$$

4.5 Survivorship bias and delisting firms

Dealing with missing values and considering survivorship bias are important aspects of dealing with data and in assessing the performance of past returns. Firms may delist from an index for a variety of reasons including; merger or acquisition and company failure. When such circumstances arise, knowing how to deal with such stocks is pivotal to the correct interpretation of results from long-term event studies, so that any conclusions drawn are not based solely on an unrepresentative sample of stocks which were strong enough to survive.

To avoid survivorship bias in their data sample, Jegadeesh and Titman (1993) include all stocks with available returns in the formation period and form the winner and loser portfolios from this selection of stocks. However, Jegadeesh and Titman (2001) exclude stocks below $5 in value to eliminate small and illiquid stocks. Rouwenhorst (1998) include all stocks with a return history of at least 12 months.

In an examination of momentum in the London Stock Exchange (LSE), Galariotis *et al.* (2007) minimise survivorship bias by including all stocks listed on the LSE. Siganos (2010) uses all stocks that traded during the rank period and if a stock delists during the test period the corresponding return is determined to be zero.

In order to minimise survivorship bias in this study, any stock that is present in the rank period is included; delisted stocks are held for the test period with the respective return determined to be zero, following the example of Jegadeesh and Titman (1993) and Siganos (2010). By following this approach any momentum returns observed will potentially be underestimated rather than over-stated as the delisting stocks due to company failure tend to be included in the loser portfolio, as the company stock price would presumably have decreased in the months prior to the company delisting[19].

4.6 Methodology pertaining to analysts' recommendations

The investment value of analysts' advice to shareholders is analysed from a number of aspects. The overall analysis time period is divided up to isolate the effects of the Internet bubble period (1995 to 2002) and the credit crisis period[20] (2005 to 2012). First, stocks are allocated to the most appropriate sector based on their unique four-digit Standard Industry Classification Code (SIC). Four-digit SICs allow for the stocks to be allocated to specific sectors rather than broad overall industry groupings to allow for in-depth analysis of analysts behaviour during specific times of crises operating in specific sectors of the market.

Observing the performance of analysts' advice during the Internet bubble; technology, telecommunications and media sector stocks are selected (hereafter, TTM stocks). Selected TTM stocks consist of twelve companies receiving analyst recommendations issued by 33 brokers. For the credit crisis period (2005 to 2012) banking, finance and investment stocks (BFI stocks) are isolated. The number of companies receiving analyst recommendations increases during this period to 33 companies. Table 4.1 presents the

[19] On average over the entire sample period 82 per cent of companies remain consistent on the FTSE from year-to year. See appendix G for details. There are 33 common constituents of the FTSE 100 between 1995 and 2015.

[20] The credit crisis period (2005 to 2012) includes the collapse of Northern Rock and the subsequent global financial crisis.

distribution of company-year observations for the TTM sector in the Internet bubble period and BFI sector in the credit-crisis period.

Table 4.2 Company observations for two sectors

Table 4.2 presents the distribution of company-year observations and all companies in the two sectors. Panel A refers to the TTM stocks for the Internet bubble period (1995-2002) whilst panel B refers to BFI sector stocks during the global credit crisis period (2005-2012). Stocks are allocated to sectors based on their four-digit SIC.

Sector	N	Company per-year observations
	Panel A	
Media	2	41
Technology	10	559
		Total= 600
	Panel B	
Financials	33	3,108
		Total= 3,108

It is evident from the figures presented in Table 4.2 that the number of observations increases greatly from the TTM stocks during the Internet bubble (Panel A) to BFI stocks during the credit crisis period (Panel B). Table 4.3 below details some statistics of the recommendation and forecast data. The mean recommendation in all instances falls within range of 2 (*buy* recommendation) some early indications of recommendations leaning towards the optimistic spectrum.

Table 4.3 Mean and Median Analysts' output

Table 4.3 presents the mean and of analysts' recommendations and forecasts. Panel A reports the statistics pertaining to recommendations for the two sub-sample periods. Panel B presents statistics for forecast data for the two sub-sample periods.

	Panel A Recommendations	
	Mean	**Median**
All sectors 1995-2002	2.26	2
TTM sector only 1995-2002	2.17	2
All sectors 2005-2012	2.03	1
BFI sector only 2005-2012	2.21	2
	Panel B Forecasts	
All sectors 1995-2002	9.97	19.35
TTM sector only 1995-2002	20.95	15.13
All sectors 2005-2012	49.74	1.30
BFI sector only 2005-2012	41.26	22.83

Firm-level returns are presented for the various recommendation categories; returns are calculated over a thirteen-month event window (*t-6, t*+6) relevant to the recommendation month *t.* The Internet bubble implosion is isolated to circa April 2000 and the bursting of the credit bubble occurs in circa September 2007. Monthly log returns are calculated using the prices obtained from the London Share Price Database (LSPD) for the relevant time periods. Cumulative raw log returns (CRRs) are calculated as well as cumulative abnormal returns (CARs) adjusted for risk using the FF3F model denoted by equation 4.4 in section 4.3.1.

The Morningstar database categorises all recommendations into one of five levels; *1-Strong buy, 2-Buy, 3-Hold, 4-Sell, 5-Strong sell.* Recommendations in the *strong buy (1)* and *strong sell (5)* categories are deemed to be the most extreme in nature. One of the advantages of using the Morningstar database is it provides the exact dates of recommendations and recommendation revisions.

In order to analyse the predictive value of analysts' advice, several measures of analysts' advice are assembled to accurately reflect the impact of their advice on potential returns. A standard partial adjustment process to past errors in forecasting future shareholder returns, as described in Nickell (1985) and Woolridge (2013) is employed.

The variables of equation 4.9 are documented in prior literature to impact on the level of return generated; for example, Stickel (1995) and Womack (1996) document the importance of recommendations; Conrad *et al.* (2006) and Ryan (2006) report recommendation revisions impact on returns, and Givoly and Lakionshok (1979) observe forecast revisions impact on returns. Furthermore, Givoly and Lakionshok (1984, pg. 40) state that 'earnings forecasts are probably next to stock recommendations, the most notable output of financial analysts', therefore, the effect of recommendations and forecasts are included in this analysis.

The predictive value of analysts' earnings forecasts and recommendations is calculated by capturing past errors and current advice from analysts, depicted by equation 4.9;

$$R_t = \alpha + \beta_1 \frac{ME_{t-1}}{P_t} + \beta_2 \frac{MF_t}{P_t} + \beta_3 \frac{\Delta MF_t}{P_t} + \beta_4 Rating_t + \beta_5 \Delta Rating_t + \beta_6 DUM_t + \varepsilon_t \quad \textbf{(4.9)}$$

Where[21]:

R_t *is* the monthly log return of stock at time t (including dividends);

ME_{t-1} is the error from co-integrating regression; (the difference in the mean forecast and the actual earning outcome of the analyst)

P_t is stock price at time t;

MF_t monthly average earnings forecast;

ΔMF_t monthly average earnings forecast revision scaled by price;

$\Delta Rating_t$ monthly average analysts' recommendation revision;

DUM_t is the dummy variable during the crisis period.

ε_t is the error term.

The dummy variable *DUM* is equal to zero before the bubble burst/financial crisis and equal to one thereafter. Therefore, TTM stocks before April 2000 are assigned $DUM=0$, and assigned one thereafter, similarly, BFI stocks are assigned dummy variable equals to zero prior to September 2007 and one thereafter. The co-integrating regression model refers to the regression of the mean forecast on the actual earning outcome for each stock in both sectors[22]. Therefore, ME_{t-1} refers to the difference in the mean forecast provided by the analyst and the actual earning outcome at time t.

The theory of Francis and Philbrick (1993, pp. 216-217) that there is a 'preference for cultivating optimistic earnings forecasts, particularly in the presence of less than favourable stock recommendations', is addressed by examining if earnings forecast revisions reinforce the analysts' recommendations. Specifically, Francis and Philbrick (1993) test whether earnings forecasts are more optimistic when stock recommendations

[21] Use of term average refers to the average across sector, i.e. average earnings forecast are the average earnings forecast across sector.
[22] Augmented Dickey-Fuller test confirms that the mean forecasting and actually monthly EPS contain a unit-root process in both bubble periods, the time-series show little sign of convergence.

are negative, i.e. earnings forecasts are more optimistic in the presence of a *sell* recommendation compared to a *hold* recommendation. Monthly average earnings forecast revisions are scaled by price for the relevant sector stocks pre and post April 2000 and September 2007 respectively, to determine if earnings forecasts are revised upwards (downwards) in the presence of a *strong sell* (*strong buy*) recommendation.

4.7 Analyst recommendation categories

The standard five point recommendation category (*1-5, strong buy-strong sell*) is used to categorise analysts' various recommendations. The various rating terms used by analysts are detailed in table 4.3. The Morningstar database post 2009 includes a change in the terms used to refer to recommendations and an increase in the number of recommendation categories, therefore analyst data post 2009 is recoded to match data prior to 2009.

Table 4.4 Rating terms per recommendation category

1	2	3	4	5
Strong Buy	Weak Buy	Hold	Weak Sell	Strong Sell
Buy	Hold/Buy	Fair	Hold/Sell	Sell
Speculate	Accumulate	Neutral	Reduce	Strong Underperform
Standout/Outperform	Speculative	Market Perform		Negative
Long-term Buy	Add	In-Line		Avoid
				Market Underperform

The frequency of recommendations per category differs through the years; Figure 4.1 illustrates the number of recommendations issued by analysts for all sectors from 1995 to 2002 (Internet bubble years). The lowest number of recommendations issued is observed in 1995 with 8,469 recommendations issued. The number of recommendations issued peak in 1998 with 23,793 recommendations issued in total across all sectors. From 1999 onwards a downward trend presents itself and in the year of the Internet bubble implosion, 2000, the number of recommendations issued falls to 18,878 and continues to decline in 2001 and 2002.

Figure 4.1 Total number of recommendations for all sectors 1995-2002

This figure presents the total number of recommendations issued for all sectors between 1995 and 2002.

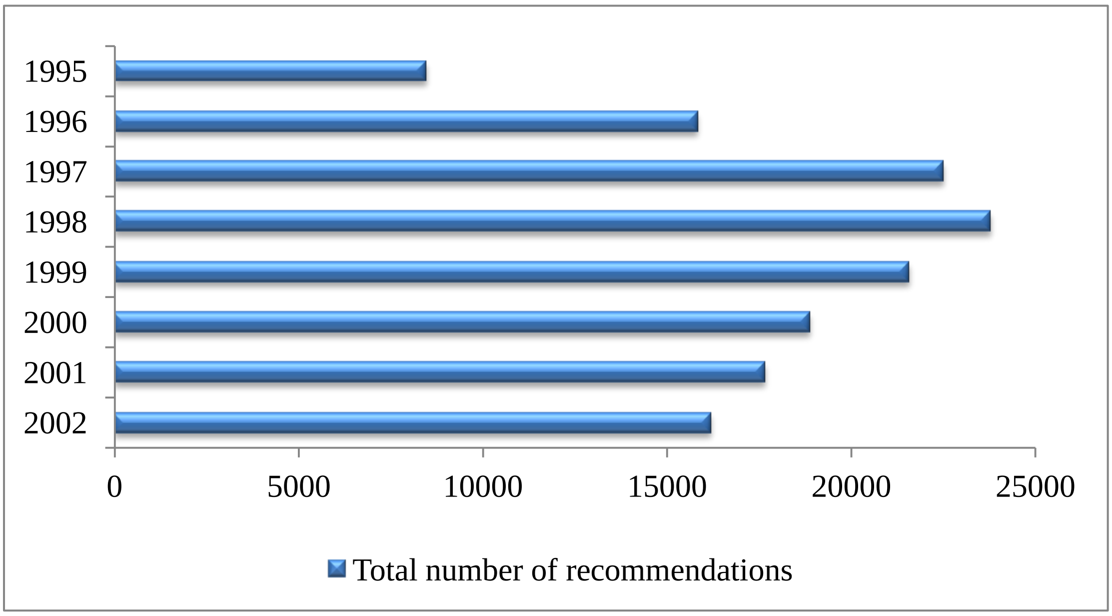


Figure 4.2 presents the total number of recommendations in the TTM sector from 1995-2002. During 1995 the least number of recommendations are recorded (477), this number increases steadily up until 1999, the year the Internet bubble burst, when the frequency of recommendations decreases from 2,251 in 1999 to 2,036 in 2000. The

number increases significantly in 2001 with 2,866 recommendations issued for stocks in the TTM sector.

Figure 4.2 Total number of recommendations in the TTM sector 1995-2002

This figure presents the total number of recommendations issued by analysts for stocks in the TTM sector (Telecommunications, Technology and Media) during the Internet bubble years 1995-2002.

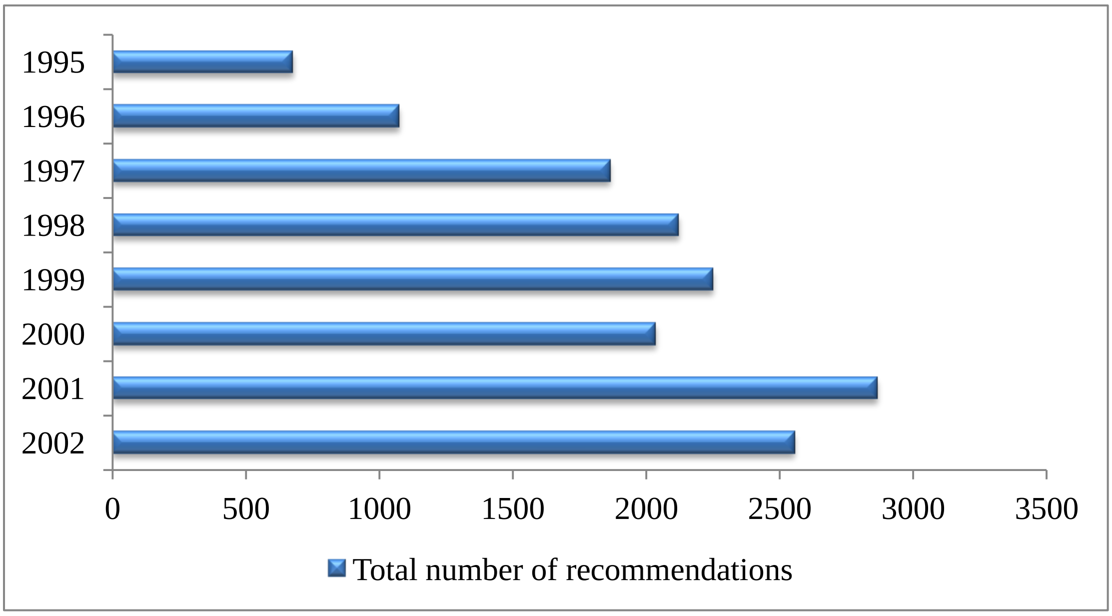


Figure 4.3 illustrates the total number of recommendations issued by analysts for all sectors during the years 2005 to 2012. The onslaught of the credit crisis in 2007 saw the number of recommendations issued for all sectors drop from 2005 levels by over 6,000 recommendations to just over 18,500 recorded in 2007. However in 2008 and 2009 the number of recommendations issued increase, reaching peak levels in 2009 with over 25,000 recommendations issued in total. However, a sharp decline in the number of

recommendations issued is observed in 2010, 2011 and 2012; with the lowest number of recommendations recorded in 2012 of 14,672.

Figure 4.3 Total number of recommendations for all sectors 2005-2012

This figure presents the total number of recommendations issued by analysts for all sectors between 2005 and 2012.

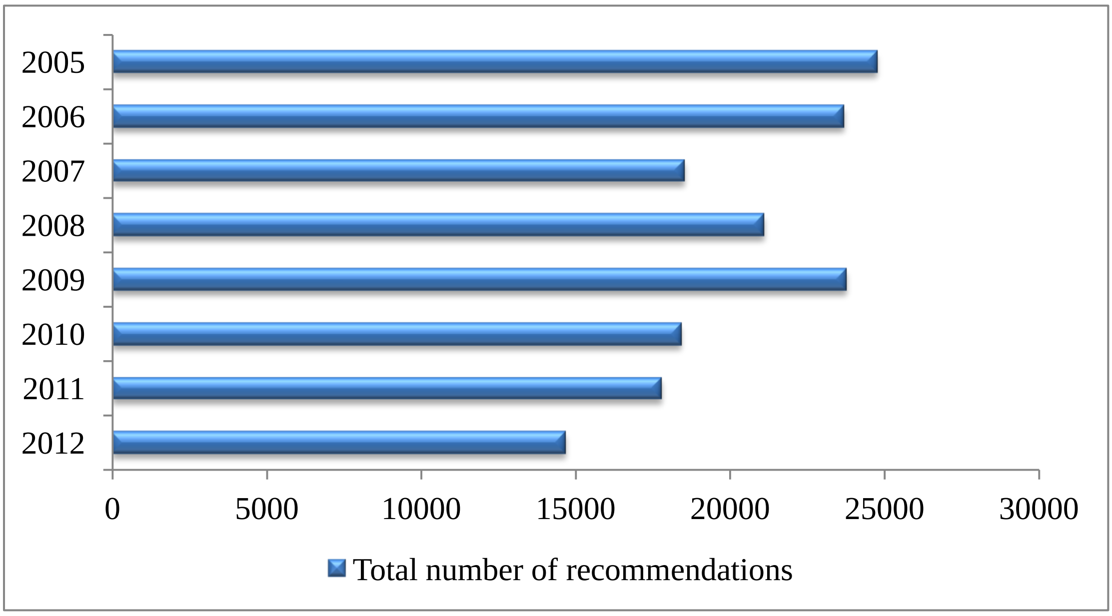
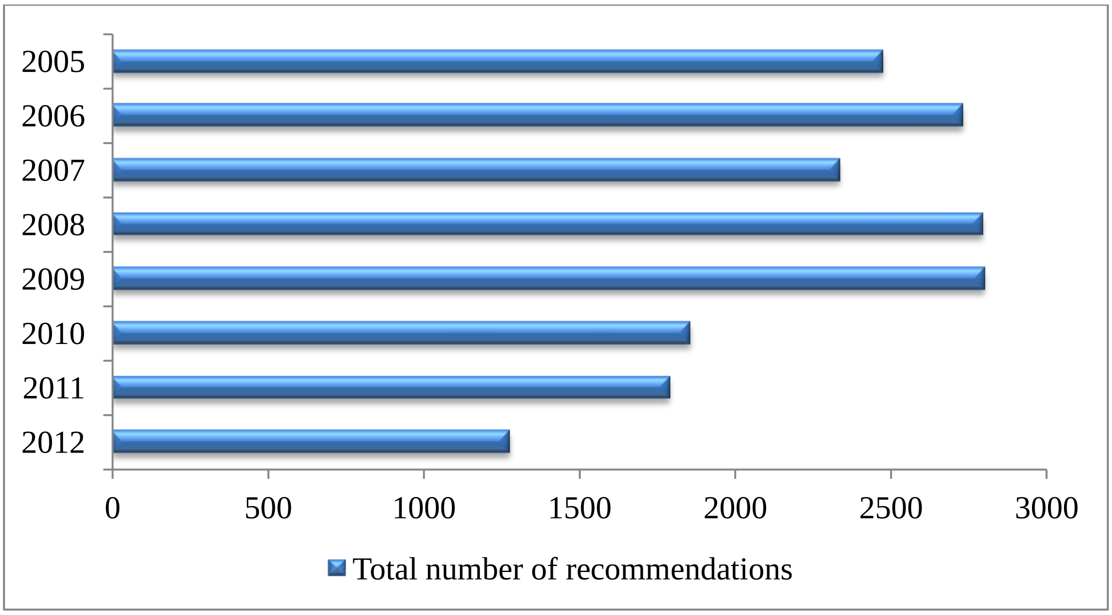


Figure 4.4 presents the number of recommendations issued by analysts for stocks in the BFI sector, during the global financial crisis years 2005 and 2012. The highest number of recommendations for stocks in the BFI sector is recorded in 2009 (2,800). From 2010 onwards the number of recommendations for stocks in the BFI sector decreases significantly, reaching the lowest level in 2012 (1,276). This may reflect the effective nationalisation of RBS and Lloyds and the restrictions placed on many other institutions seeking financial support from the state.

Figure 4.4 Total number of recommendations in the BFI sector 2002-2012

This figure presents the total number of recommendations issued by analysts for stocks in the BFI sector (Banking, Finance and Investment stocks) during the global financial crisis years 2005 to 2012.



4.8 Chapter summary

This chapter detailed the data and methodology used to answer the principal research questions of this study. Databases including the LSPD, ThomsonONE and the Morningstar extracted data file are used to collect the various data required for this study. Stocks listed on the FTSE100 between 1995 and 2015 are included in the sample.

The method used to investigate the profitability of the strength-rule strategy in the UK stock market is outlined; the method outlined by Jegadeesh and Titman (1993) is largely followed. The method of Moskowitz and Grinblatt (1999) is detailed with the aim of examining the profitability of industry momentum. The return generating models are also presented.

Methods used to determine the predictive value of analysts' recommendations and forecasts are also described. Evidence of the frequency of recommendations both overall and in the relevant sectors during specific times is presented.

Chapter Five – Findings

5.1 Introduction

The main findings of the study pertaining to momentum in the UK stock market and the behaviour and accuracy of analysts during times of economic chaos are detailed in chapter five. Section 5.2 details results concerning the momentum study. Within section 5.2, sub-section 5.2.2 details the results of the strength-rule strategy for individual stocks for the overall time-frame of study (1995 to 2015); sub-section 5.2.3 documents the findings relevant to the study of industry momentum in the overall time-period under analysis (1995 to 2015). The main findings uncovered during analysis of the sub-sample periods are presented in section 5.3. Results applicable to the output of analysts are documented in section 5.4.

5.2 Results of Strength-rule strategy

This section reports the findings for the strength-rule strategy during the overall time-frame of study (1995-2015) using the models outlined in section 4.3. The momentum return, i.e. winners minus losers, are reported as are the returns of the winner and loser portfolios; to determine if the momentum return is primarily driven by the performance of either the winner or loser portfolio.

5.2.2 Individual momentum strategies

Table 5.1 and table 5.2 present the results of the strength-rule strategy for individual firms for the period 1995 to 2015, obtained using the FF3F model described in equation

4.4. Table 5.1 presents the results with no month skipped between the rank and hold periods and table 5.2 presents the returns for strength-rule strategies with a month's gap between the rank and hold periods (referred to as the skip-strategy). The return of the winner and loser portfolios as well as the average monthly return for winners minus losers (momentum) is reported. The abnormal returns of 30 different rank and hold periods are reported.

The optimum strength-rule strategy comprises of a three-month rank and 24-month hold strategy, generating an average monthly return of 3.1 per cent at a 1 per cent level of significance, when no month is skipped between the rank and hold periods. The winner and loser portfolios contribute evenly to the abnormal return, each contributing approximately 50 per cent[23]. It is noticeable for the full sample that as the length of rank period increases the abnormal return decreases. Negative returns are observed in six rank/hold combinations although they are not statistically significant.

[23] See appendix H for details concerning the consistency of winners/losers in consecutive periods.

Table 5.1 Strength-rule strategy returns for individual firms 1995-2015

This table reports average monthly returns for the strength-rule strategy for individual stocks for the period 1995 to 2015, with *no month skipped between rank and hold period.* Cumulative average abnormal winner and loser portfolio returns as well as CAR_w-CAR_L for rank and hold periods ranging from three to 24 months are reported. The returns are adjusted using the 3-factor Fama-French Model (1993) outlined in equation 4.4, based on equally-weighted portfolios[24]. Two-tailed t-statistics are reported in parentheses. T-statistics are estimated using the method of De Bondt and Thaler (1985).

		Hold period (Months)					
Rank Period (months)		**3**	**6**	**9**	**12**	**18**	**24**
3	**W**	0.000	0.005	0.004	0.008	0.014	0.016
	L	-0.000	-0.003	-0.008	-0.017	-0.015	-0.015
	W-L	0.000	0.008**	0.012**	0.024*	0.028*	0.031*
		(0.05)	(2.13)	(2.41)	(4.12)	(3.68)	(3.39)
6	**W**	-0.000	0.002	0.005	0.007	0.008	0.008
	L	-0.002	-0.001	-0.005	-0.004	-0.003	-0.003
	W-L	0.002	0.003**	0.009*	0.011*	0.011***	0.011***
		(1.03)	(2.11)	(4.56)	(3.73)	(3.06)	(1.82)
9	**W**	-0.001	-0.001	0.001	0.004	0.003	0.002
	L	-0.002	-0.002	-0.003	-0.007	-0.001	-0.002
	W-L	0.001	0.001	0.004	0.005	0.004	0.004
		(0.46)	(0.48)	(1.15)	(1.29)	(0.74)	(0.09)
12	**W**	0.000	0.000	0.002	0.000	-0.000	-0.001
	L	0.001	-0.001	-0.002	-0.003	-0.000	-0.000
	W-L	-0.001	0.001	0.004	0.003	-0.000	-0.000
		(0.63)	(0.45)	(1.42)	(0.93)	(0.18)	(0.08)
18	**W**	0.001	0.000	-0.000	-0.000	-0.004	-0.003
	L	-0.003	-0.003	-0.003	-0.002	-0.001	0.001
	W-L	0.003	0.003	-0.003	0.002	-0.003	-0.004
		(1.72)	(1.12)	(1.04)	(0.69)	(0.77)	(0.84)

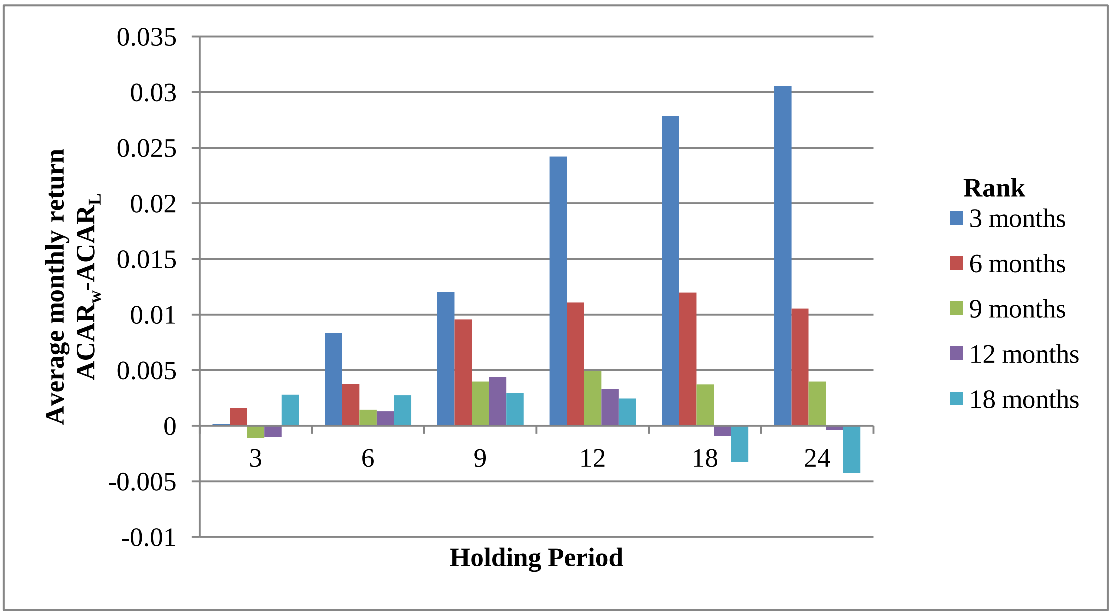
*significant at the 1% level
**significant at the 5% level
***significant at the 10% level

[24] Results were not substantially altered with the use of value-weighted portfolios.

The performances of CARw – CAR_L for each rank and hold period is displayed in figure 5.1. It is evident that a short rank and longer hold period is the optimum strategy to maximise trading profits. The Sharpe ratios also reflect this, see appendix F for Sharpe Ratios for all strategies. A Sharpe ratio of 0.40 is recorded for the 3/24 strategy, only slightly lower than the 3/12 and 3/18 strategies that also produce positive momentum returns.

Figure 5.1 Returns to strength-rule strategies for all rank and hold combinations (1995-2015) Individual stocks

This figure presents the average monthly returns of the strength-rule strategy for the entire sample period 1995 to 2015 for all rank and hold combinations, with no gap between the rank and hold periods. Equally-weighted portfolios consist of the top and bottom ranked individual stocks.



As figure 5.1 illustrates, for the three-month rank periods there is no evidence of reversal. However for the six, nine, twelve and 18 month rank periods evidence of partial reversal is evident when the hold period exceeds twelve months.

Table 5.2 Strength-rule strategy returns for individual firms 1995-2015

The table reports average monthly returns for the strength-rule strategy for individual stocks for time period 1995 to 2015, with a *month skipped* between the rank and hold period. Cumulative average abnormal winner and loser portfolio returns as well as CAR_w-CAR_L for rank and hold periods ranging from three to 24 months are reported. The returns are adjusted using the 3-factor Fama-French Model (1993) outlined in equation 4.4, based on equally-weighted portfolios. Two-tailed t-statistics are reported in parentheses. T-statistics are estimated using the method of De Bondt and Thaler (1985).

		Hold period (Months)					
Rank Period (months)		**3**	**6**	**9**	**12**	**18**	**24**
3	**W**	0.004	0.006	0.007	0.009	0.014	0.018
	L	-0.001	-0.007	-0.011	-0.016	-0.017	-0.016
	W-L	0.005*	0.013*	0.018*	0.025*	0.030*	0.033*
		(2.21)	(3.56)	(3.72)	(4.17)	(4.28)	(3.88)
6	**W**	-0.001	0.003	0.005	0.005	0.007	0.006
	L	-0.003	-0.003	-0.006	-0.004	-0.004	-0.002
	W-L	0.002	0.006**	0.011*	0.009**	0.011***	0.008
		(1.17)	(2.51)	(3.26)	(2.03)	(1.92)	(1.13)
9	**W**	-0.001	-0.001	0.003	0.002	0.003	0.006
	L	-0.002	-0.003	-0.003	-0.002	-0.002	-0.002
	W-L	0.001	0.002	0.006***	0.004	0.005	0.008
		(0.30)	(0.73)	(1.81)	(1.07)	(1.17)	(0.81)
12	**W**	-0.001	-0.000	0.001	-0.002	-0.003	-0.002
	L	-0.000	-0.002	-0.003	-0.001	-0.002	-0.000
	W-L	-0.000	0.002	0.004	-0.001	-0.001	-0.002
		(0.12)	(0.55)	(1.32)	(0.27)	(0.29)	(0.43)
18	**W**	-0.000	-0.000	0.001	-0.002	-0.004	-0.005
	L	-0.003	-0.003	-0.003	-0.003	-0.011	-0.000
	W-L	0.003***	0.002	0.004	0.001	-0.003	-0.005
		(1.80)	(1.09)	(1.75)	(0.18)	(0.77)	(1.02)

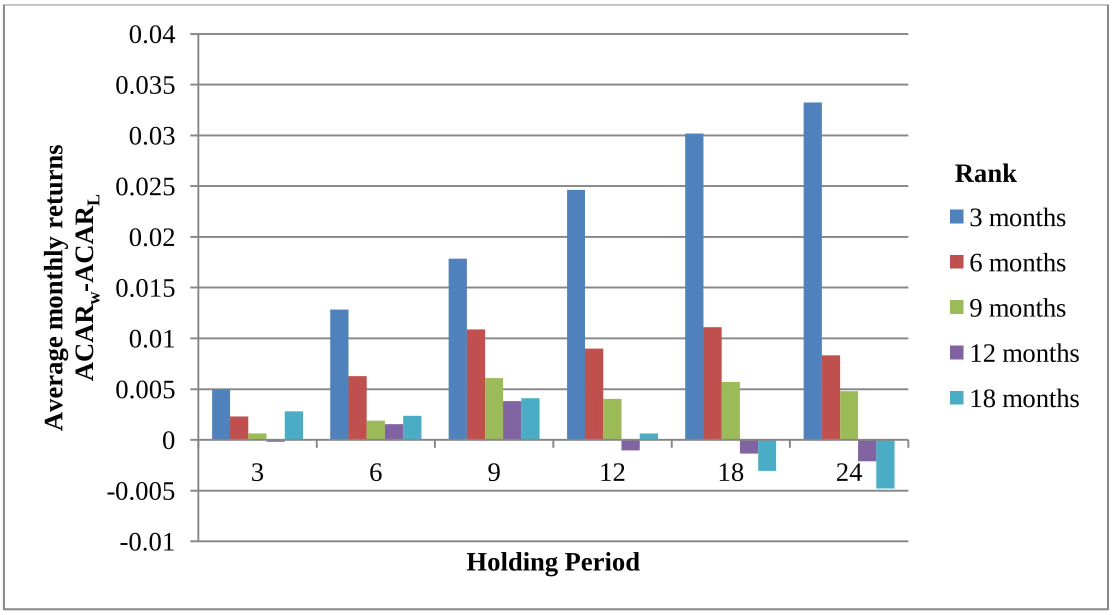
*significant at the 1% level
**significant at the 5% level
***significant at the 10% level

As table 5.2 illustrates the optimum rank/hold combination for the skip-strategy also consists of a three-month rank and 24-month hold period, generating a marginally higher average monthly return of 3.3 per cent, which is statistically significant at the 1 per cent level. The winner portfolio contributes just over half (55 per cent) to the abnormal return. The Sharpe ratio is slightly higher for the skip-strategy at 0.45.

Figure 5.2 presents the average monthly returns of the skip-strategy for all rank and hold combinations. It is evident that even with a month's gap between the rank and hold period, a combination of short rank and long hold period is the optimum strategy. In general the returns of the strength-rule strategy and the skip-strategy do not generate materially different returns.

Figure 5.2 Returns to strength-rule strategies for all rank and hold combinations (1995-2015) Individual stocks

This figure presents the average monthly returns for the strength-rule strategy for the entire sample period 1995 to 2015 for all rank and hold combinations, with *a month's gap* between the rank and hold periods. Equally-weighted portfolios consist of the top and bottom ranked stocks.

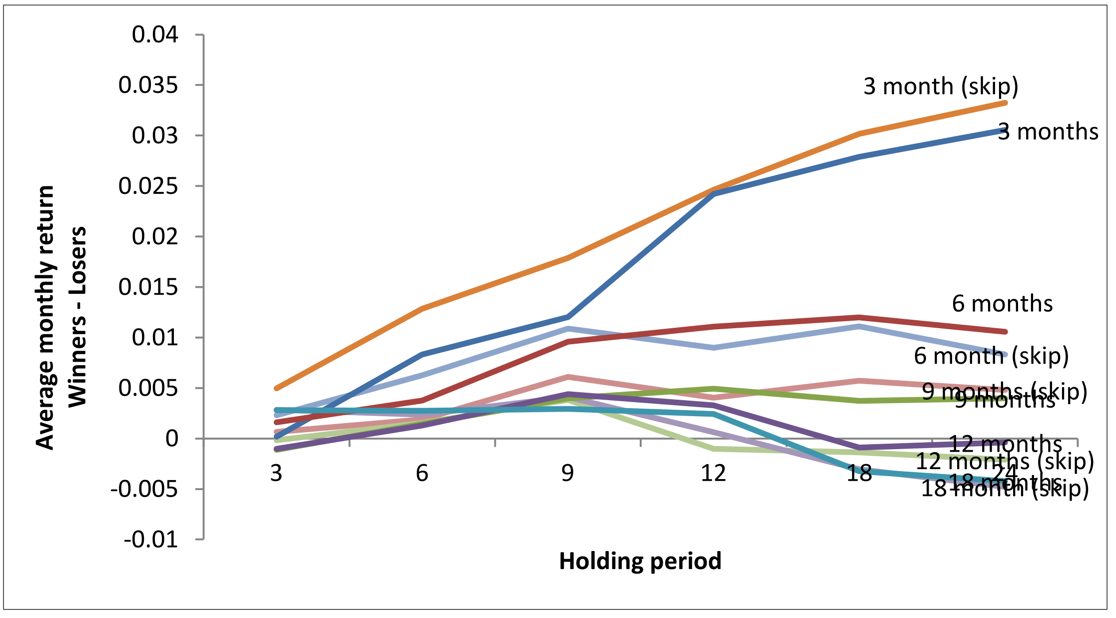


Using the skip-strategy evidence of reversal for three-month ranked stocks is not present. However, for the other rank periods (6, 9, 12 and 18 months) partial reversal is evident when the hold period is in excess of twelve months, similar to the findings of the regular momentum strategy.

As stated previously, little difference exists between the returns of the strength-rule strategy and the skip-strategy. Figure 5.3 diagrammatically presents the difference between the outcomes of the strength-rule strategy and the skip-strategy.

Figure 5.3 Comparison of $CAR_w - CAR_L$

Figure 5.3 presents the average monthly returns of the strength-rule strategy for individual stocks with both a month's gap and no month's gap (skip-strategy) between rank and hold periods for the entire time period 1995-2015. Equally-weighted portfolios consist of the top and bottom ranked stocks.



It would appear that both the conventional strategy and skip-strategy exhibit similar patterns of returns. With a rank period other than three months and the hold period extending beyond twelve months selected, the momentum return (winner-loser) declines, pointing to evidence of reversal in the long-term. However, for a strategy consisting of a three-month rank period, returns continue to increase as the length of hold period increases.

5.2.3 Industry momentum strategies

This section details the abnormal returns recorded for the strength-rule strategy when portfolios are formed on the basis of industry performance as opposed to individual stock performance. The portfolios are formed following the steps outlined in section 4.3.3 and the returns are calculated using the FF3F model presented in equation 4.4. Table 5.3 presents the results when no month is skipped between the rank and hold periods for the overall time period 1995 to 2015. The abnormal return of the strength-rule strategy is reported as is the return of the winner and loser industry portfolios[25].

The optimum industry strength-rule strategy consists of a three-month rank period and twelve-month hold period (3/12) with an average monthly return of 1.7 per cent observed, which is statistically significant at 1 per cent. The industry return of 1.7 per cent is lower than the 3.1 per cent registered for individual stocks. The winner and loser portfolios contribute evenly to the optimum strategy. Notably, the agriculture, forestry, fishing and construction industries appear 33 times in the winner portfolio, when ranked on the basis of three-month returns. The agriculture, fishing and forestry industry also appear most frequently in the loser portfolio.

The six-month industry ranking periods perform comparatively well also, with a six-month ranking period generating returns in excess of 1 per cent when the holding period extends beyond nine months. Observing the Sharpe ratios, it is noticeable that Sharpe ratios are on average higher for the six-month rank period compared to the three-month

[25] Appendix I contains details of industry consistency in the winner/loser portfolios. See appendix J for breakdown in the frequency of industry appearance in the winner and loser portfolios.

rank period. Furthermore, positive momentum returns are recorded in all but one combination period (18/24) for industry momentum from 1995-2015.

Table 5.3 Strength-rule strategy returns for industries 1995-2015

This table reports average monthly returns for the strength-rule strategy for industries during the time period 1995 to 2015, with *no month skipped* between rank and hold period. Cumulative average abnormal winner and loser portfolio returns as well as CAR_w-CAR_L for rank and hold periods ranging from three to 24 months are reported. The returns are adjusted using the 3-factor Fama-French Model (1993) outlined in equation 4.4, based on equally-weighted portfolios. Two-tailed t-statistics are reported in parentheses. T-statistics are estimated using the method of De Bondt and Thaler (1985).

		Hold period (Months)					
Rank Period (months)		**3**	**6**	**9**	**12**	**18**	**24**
3	**W**	0.002	0.006	0.006	0.008	0.006	0.010
	L	-0.001	-0.004	-0.005	-0.009	-0.004	-0.005
	W-L	0.003	0.010*	0.011**	0.017*	0.010	0.015**
		(1.27)	(2.95)	(2.32)	(3.29)	(1.63)	(2.20)
6	**W**	0.002	0.005	0.006	0.007	0.006	0.006
	L	-0.003	-0.004	-0.005	-0.007	-0.008	-0.009
	W-L	0.005*	0.009*	0.011*	0.014*	0.014*	0.015*
		(2.71)	(3.57)	(3.26)	(3.57)	(3.51)	(3.07)
9	**W**	0.001	0.004	0.004	0.004	0.002	0.003
	L	-0.001	-0.001	-0.003	-0.002	0.000	0.001
	W-L	0.002	0.005**	0.007**	0.006***	0.002	0.002
		(1.00)	(2.35)	(2.56)	(1.98)	(0.75)	(0.58)
12	**W**	0.002	0.002	0.001	0.003	0.003	0.002
	L	-0.000	-0.002	-0.005	-0.003	-0.004	-0.003
	W-L	0.002***	0.004	0.006**	0.006**	0.007**	0.005
		(1.82)	(1.56)	(2.23)	(2.49)	(2.39)	(1.32)
18	**W**	0.000	0.002	0.002	0.003	0.001	0.002
	L	0.000	-0.000	-0.001	-0.001	-0.001	0.002
	W-L	0.000	0.003	0.003***	0.004	0.002	-0.000
		(0.00)	(1.73)	(1.82)	(1.57)	(0.88)	(0.16)

*significant at the 1% level
**significant at the 5% level
***significant at the 10% level

Figure 5.4 presents the average monthly returns of an industry momentum strategy with no month's gap between the rank and hold periods. Overall, evidence of reversal is less apparent for industry momentum particularly for the three and six-month ranking periods. However, partial reversal is observed for the nine, twelve and 18-month rank periods.

Figure 5.4 Returns to strength-rule strategies for all rank and hold combinations (1995-2015) Industry portfolios

This figure presents the average monthly returns for the strength-rule strategy for the entire sample period 1995 to 2015 for all rank and hold combinations, with *no gap* between the rank and hold periods. Equally-weighted portfolios consist of the top and bottom ranked industries.

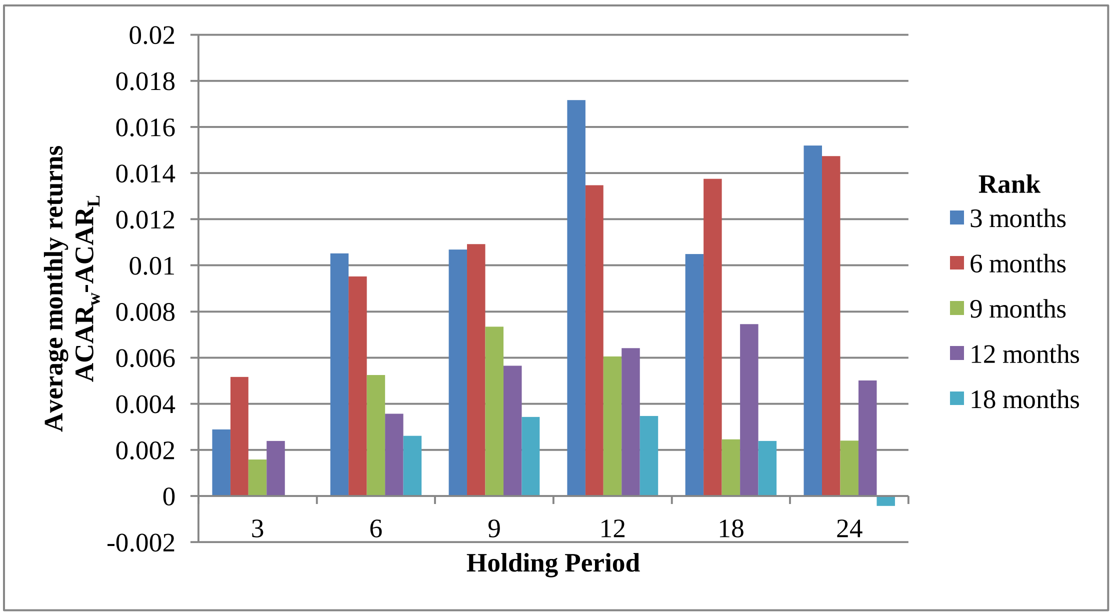


Table 5.4 presents the momentum return of the industry skip-strategy. For the industry skip-strategy, an average monthly return of 1.5 per cent is registered for two strength-rule strategies, 3/12 and 3/24, statistically significant at the 1 and 5 per cent levels of significance. The average monthly industry return of 1.5 per cent is less than the 3.3 per cent registered for individual momentum. During the optimum 3/12 strategy winners

and losers contribute relatively evenly to the overall return. However, for the 3/24 strategy the performance of the winner portfolio contributes 73 per cent of the overall return. No negative returns are recorded for the industry skip-strategy between 1995 and 2015.

Table 5.4 Strength-rule strategy returns for industries 1995-2015

This table reports average monthly returns for the strength-rule strategy for industries for the period 1995 to 2015, with a month *skipped between rank and hold period*. Cumulative average abnormal winner and loser portfolio returns as well as CAR_w-CAR_L for rank and hold periods ranging from three to 24 months are reported. The returns are adjusted using the 3-factor Fama-French Model (1993) outlined in equation 4.4, based on equally-weighted portfolios. Two-tailed t-statistics are reported in parentheses. T-statistics are estimated using the method of De Bondt and Thaler (1985).

		Hold period (Months)					
Rank Period (months)		**3**	**6**	**9**	**12**	**18**	**24**
3	**W**	0.004	0.006	0.007	0.007	0.005	0.011
	L	-0.003	-0.005	-0.006	-0.008	-0.004	-0.005
	W-L	0.007*	0.011*	0.013*	0.015*	0.009	0.015**
		(3.01)	(3.19)	(2.85)	(2.76)	(1.44)	(2.27)
6	**W**	0.000	0.004	0.003	0.005	0.003	0.006
	L	-0.003	-0.003	-0.006	-0.004	-0.005	-0.007
	W-L	0.003**	0.007**	0.009**	0.009**	0.008**	0.013**
		(2.07)	(2.53)	(2.69)	(2.31)	(2.20)	(2.65)
9	**W**	0.002	0.004	0.004	0.004	0.003	0.002
	L	-0.02	-0.002	-0.003	-0.001	-0.000	-0.001
	W-L	0.004**	0.006**	0.007**	0.005***	0.003	0.001
		(2.36)	(2.41)	(2.86)	(1.89)	(0.94)	(0.54)
12	**W**	-0.000	0.001	-0.001	0.002	0.001	0.002
	L	-0.002	-0.002	-0.004	-0.002	-0.003	-0.001
	W-L	0.002	0.003	0.003	0.004	0.004	0.003
		(1.82)	(1.56)	(2.23)	(2.49)	(2.39)	(1.32)
18	**W**	0.000	0.002	0.002	0.003	0.002	0.002
	L	-0.002	-0.001	-0.003	-0.002	-0.001	0.001
	W-L	0.002	0.003**	0.005*	0.005**	0.003***	0.001
		(0.00)	(1.73)	(1.82)	(1.57)	(0.88)	(0.16)

*significant at the 1% level
**significant at the 5% level
***significant at the 10% level

Figure 5.5 presents the average monthly return of the industry skip-strategy. Evidence of partial reversal is present for nine, twelve and 18-month ranking periods, three-month ranking periods show signs of reversal after 18-months but this recovers in the 24-month period.

Figure 5.5 Returns to strength-rule strategies for all rank and hold combinations (1995-2015) Industry portfolios

This figure presents the average monthly returns for the strength-rule strategy for the entire sample period 1995 to 2015 for all rank and holds combinations, with a *month's gap* between the rank and hold periods. Equally weighted portfolios consist of the top and bottom ranked industries.

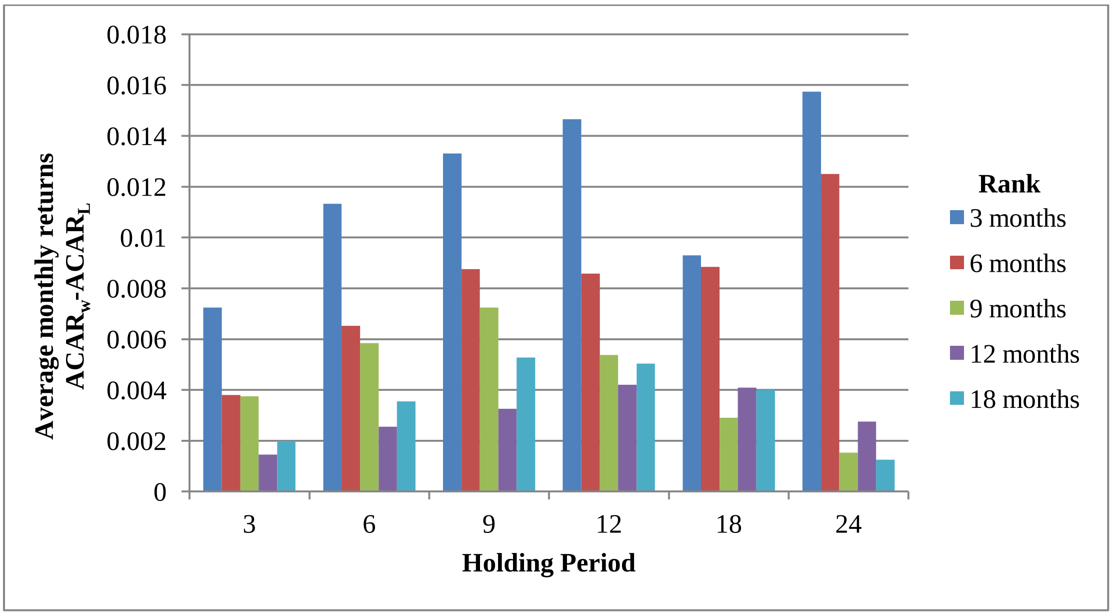
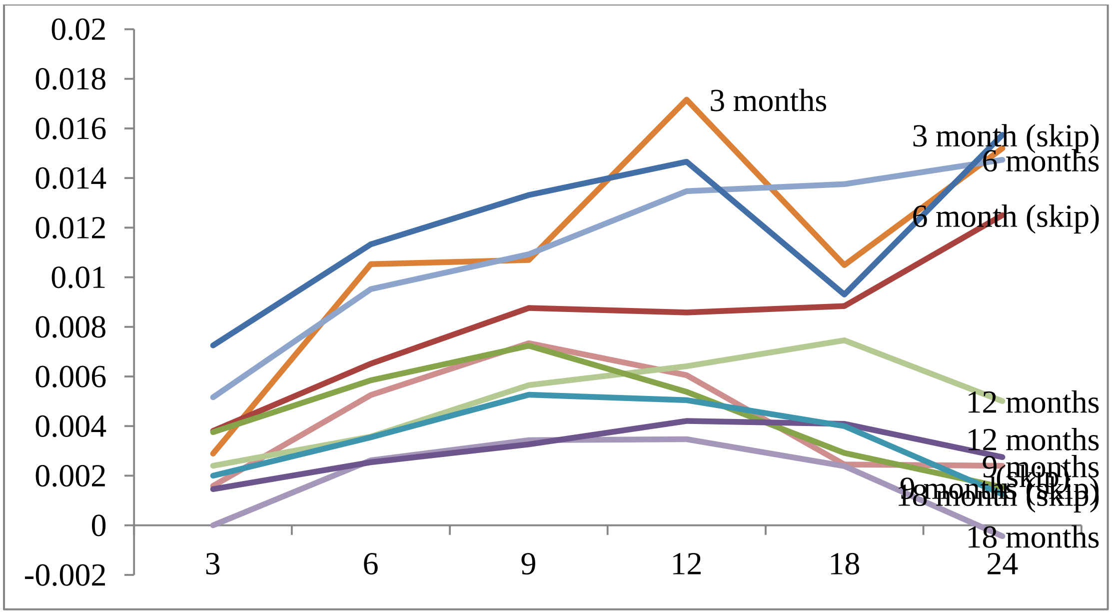


Figure 5.6 graphically compares the performance of the conventional industry strength-rule strategy and the industry skip-strategy between 1995 and 2015. Similar to the individual momentum results, the presence of a month's gap between the rank and hold

periods for industry momentum, does not appear to significantly impact the level of returns generated.

Figure 5.6 Comparison of $CAR_w - CAR_L$

Figure 5.3 presents the average monthly returns of the strength-rule strategy with both a month's gap and no month's gap between rank and hold periods for the entire time period 1995-2015. Equally-weighted portfolios consist of the top and bottom ranked industries.



Negative returns are only recorded in 1/30 rank and hold combinations when portfolios are formed on the basis of industries, as opposed to 6/30 when portfolios are formed using individual stocks.

5.3 Sub –period analysis

This section presents the returns generated from the strength-rule strategy during the sub-period analysis, covering the Internet bubble and global financial crisis periods. There is no gap between the rank and hold period for the sub-period analysis, as no significant difference was found between the strategies during the analysis of the overall time period (1995-2015). Returns are generated using the FF3F model outlined in equation 4.4 previously. The global financial crisis period relates to the years 2005 to 2012. The Internet bubble or dot.com bubble includes the years 1995 through to 2002. Table 5.5 presents the returns of the strength-rule strategy during the global financial crisis period for portfolios formed on the bases of individual stocks. For brevity the winner and loser portfolio returns are not tabulated but can be found in appendix B.

Table 5.5 Strength-rule strategy returns for individual stocks for global financial crisis period (2005 - 2012)

Table 5.5 presents the average monthly returns of the strength-rule strategy for portfolios formed on the basis of individual stocks for the sub-period 2005 to 2012. CAR_w-CAR_L returns are reported. The performance of winner and loser portfolios can be found in appendix B. T-statistics are reported in parenthesis and calculated using the method of De Bondt and Thaler (1985).

Rank/Hold period (months)	**3**	**6**	**9**	**12**	**18**	**24**
3	-0.005	0.000	-0.002	0.010	0.007	0.032***
	(0.87)	(0.00)	(0.28)	(1.08)	(0.61)	(2.05)
6	-0.010***	-0.008	-0.012***	-0.008	-0.003	0.005
	(2.09)	(1.20)	(1.93)	(0.99)	(0.36)	(0.39)
9	0.000	0.005	0.005	0.002	0.003	0.004
	(0.15)	(1.49)	(1.42)	(0.36)	(0.42)	(0.35)
12	-0.003	-0.002	-0.003	-0.002	-0.005	-0.006
	(0.99)	(0.40)	(0.93)	(0.36)	(1.46)	(1.09)
18	-0.002***	0.000	0.001	0.004	-0.007	0.000
	(2.38)	(0.02)	(0.55)	(0.81)	(0.86)	(0.05)

*significant at 1% level
**significant at 5% level
***significant at 10% level

The optimum strength-rule strategy for the global financial crisis period consists of a three-month rank and 24-month hold period (3/24), generating an average monthly return of 3.2 per cent, statistically significant at the 10 per cent level. This 3/24 combination is by far the most profitable combination during this period, as the next best performing strategy (3/12) generates a considerably smaller monthly return of 1 per cent.

Furthermore, several occurrences of negative returns are recorded during this period; half of the rank/hold combinations generate a negative average monthly return. For instance during a 6/9 strategy the average monthly return is negative 1.2 per cent. The average monthly return of 3.2 per cent generated during the global financial crisis period is almost identical to the 3.1 per cent monthly return generated during the overall time frame. The performance of the strength-rule strategy during the global financial crisis period is dependent on the performance of the winner portfolio, as the loser portfolios do not produce the negative returns desired in the majority of rank/hold combinations.

Figure 5.7 presents the returns of the strength-rule strategy for all rank and hold combinations. No clear pattern of returns is discernible during the global financial crisis period, the lack of consistency in returns is fortified by the poor performance of the strategy once the 3/24 period is excluded. Excluding the performance of the 3/24 strategy, other strategies significantly underperform and positive returns are only achieved with less than 1 per cent frequency.

Figure 5.7 Returns to strength-rule strategies for individual stocks for Global financial crisis period 2005-2012

Figure 5.7 presents the returns of the strength-rule strategy for individual stocks during the years 2005-2012 for all rank and hold combinations.

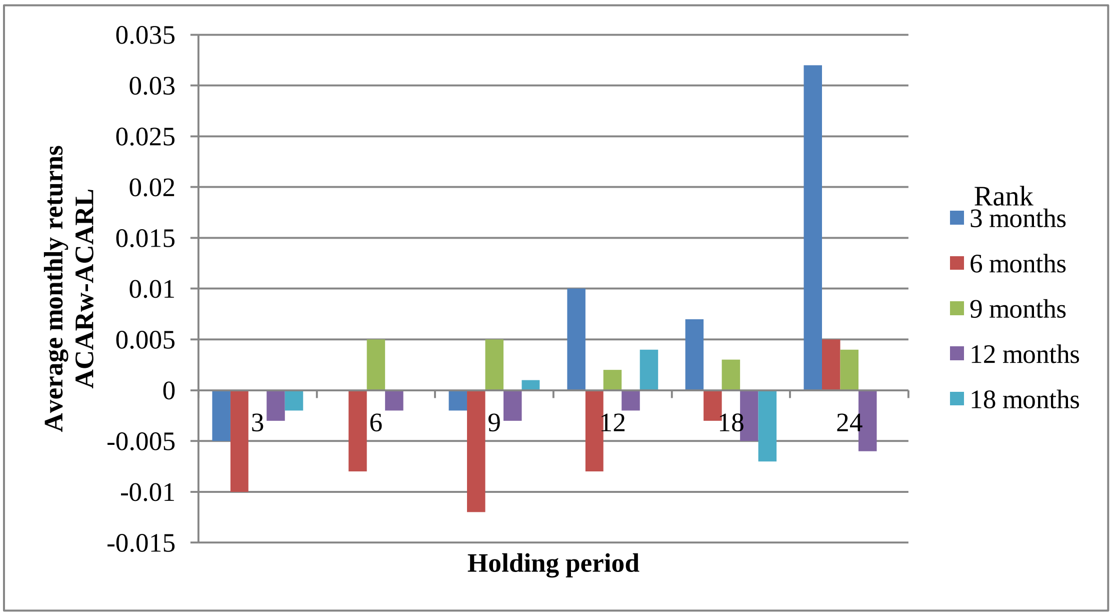


Table 5.6 presents the returns of the strength-rule strategy for individual stocks during the Internet bubble period (1995-2002). A 3/18 combination is the optimum strength-rule strategy, generating a monthly return of 5.4 per cent, statistically significant at the 1 per cent level. The return of 5.4 per cent is 2.3 percentage points greater than the optimum return generated during the overall time frame. The winner portfolio contributes over 55 per cent of the abnormal return and during the Internet bubble period the loser portfolio returns generate a negative return as expected. A Sharpe ratio of 0.93 is recorded for the 3/18 strategy, on several occasions substantially higher Sharpe ratios are recorded for the Internet bubble period compared to other time periods.

Table 5.6 Strength-rule strategy returns for individual stocks for Internet bubble period (1995 - 2002)

Table 5.6 presents the average monthly returns of the strength-rule strategy (momentum returns) for portfolios formed on the basis of individual stocks for the sub-period 1995-2002. CAR_w-CAR_L returns are reported. The performance of winner and loser portfolios can be found in appendix C. T-statistics are reported in parentheses and calculated using the method of De Bondt and Thaler (1985).

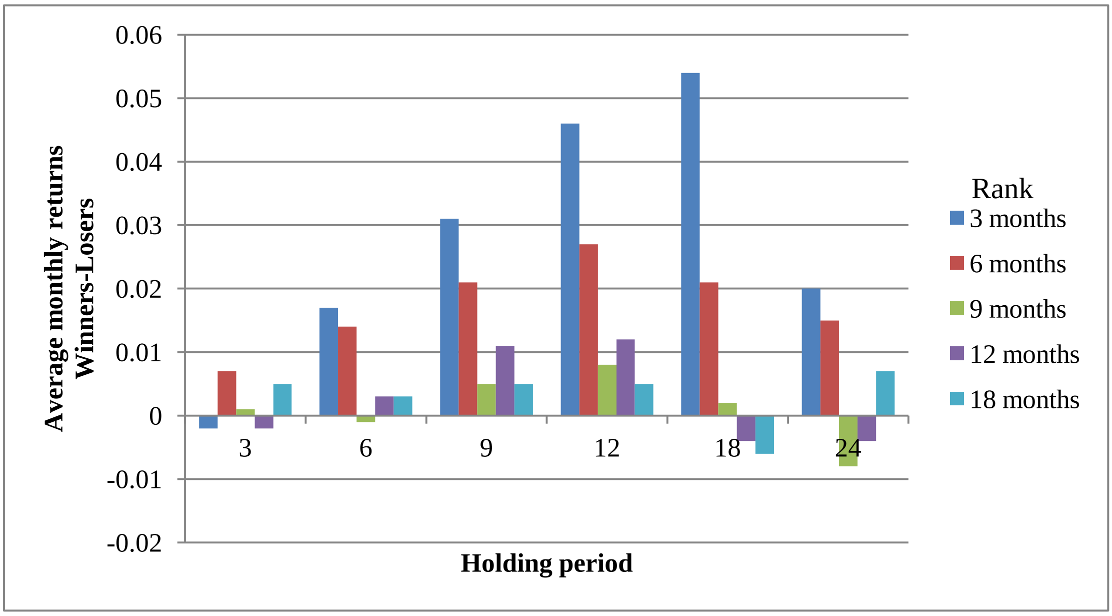
Rank/Hold period (months)	3	6	9	12	18	24
3	-0.002	0.017**	0.031*	0.046*	0.054*	0.020
	(0.49)	(2.74)	(4.05)	(5.06)	(4.73)	(1.57)
6	0.007	0.014*	0.021*	0.027*	0.021**	0.015
	(1.71)	(3.33)	(4.35)	(4.76)	(2.47)	(1.25)
9	0.001	-0.001	0.005	0.008	0.002	-0.008
	(0.19)	(0.27)	(1.07)	(1.07)	(0.17)	(0.70)
12	-0.002	0.003	0.011***	0.012***	-0.004	-0.004
	(0.74)	(0.75)	(1.97)	(2.05)	(0.32)	(0.41)
18	0.005	0.003	0.005	0.005	-0.006	0.007
	(1.77)	(0.67)	(0.95)	(0.78)	(0.54)	(1.67)

*significant at 1% level
**significant at 5% level
***significant at 10% level

Figure 5.8 presents the returns to the strength-rule strategy for all rank and hold periods during the Internet bubble period. Evidence of reversal is apparent in all but the 18-month ranking strategy; all other strategies show evidence of reversal after a period of 18 months. In general, the performance of individual momentum strategies is far more consistent when compared to the global financial crisis period.

Figure 5.8 Returns to strength-rule strategies for individual stocks for Internet bubble period 1995-2002

Figure 5.8 presents the returns of the strength-rule strategy for individual stocks during the years 1995-2002 for all rank and hold combinations.



The results of the strength-rule strategy for portfolios formed on the basis of industries during the global financial crisis period are presented in table 5.7. Overall momentum return is presented in table 5.7 and the returns to winner and loser portfolios are included in appendix C. The industry strength-rule strategy does not generate returns in excess of 1 per cent during the global financial crisis period. Notably, it is only during the global financial crisis period that the optimum investment strategy does not consist of a three-month rank period. The optimum strategy being either 9/6 or 18/18, both generating a return of 0.9 per cent, significantly less than 1.7 per cent industry return generated in the overall time period.

Table 5.7 Strength-rule strategy returns industries during the global financial crisis period (2005-2012)

This table presents the average monthly returns of the strength-rule strategy (momentum returns) for portfolios formed on the basis of industries for the sub-period 2005 to 2012. CAR_w-CAR_L returns are reported. The performance of winner and loser portfolios can be found in appendix D. T-statistics are reported in parenthesis and calculated using the method of De Bondt and Thaler (1985).

Rank/Hold period (months)	**3**	**6**	**9**	**12**	**18**	**24**
3	-0.008	-0.005	0.001	-0.005	-0.005	0.005
	(1.51)	(0.62)	(0.07)	0.39)	(0.37)	(0.39)
6	-0.005	0.002	-0.003	0.000	0.000	0.009
	(1.25)	(0.29)	(0.41)	(0.05)	(0.29)	(0.87)
9	0.004	0.009***	0.002	-0.003	-0.002	-0.003
	(1.57)	(2.03)	(0.54)	(0.46)	(0.37)	(0.38)
12	-0.003	0.000	-0.000	-0.000	0.013	0.009
	(0.83)	(0.09)	(0.04)	(0.01)	(1.79)	(1.25)
18	0.000	0.006	0.002	0.002	0.009**	0.008***
	(0.06)	(1.55)	(0.45)	(0.32)	(5.83)	(2.41)

*significant at 1% level
**significant at 5% level
***significant at 10% level

Figure 5.9 illustrates the returns of the industry strength-rule strategies during the global financial crisis period. Similar to individual strength-rule strategies during this time period, no obvious pattern of returns is discernible. The three-month rank strategy fails to produce significant returns on any occasion.

Figure 5.9 Returns to strength-rule strategies for industries for Global financial crisis 2005-2012

Figure 5.9 presents the returns of the strength-rule strategy for industries during the years 2005-2012 for all rank and hold combinations.

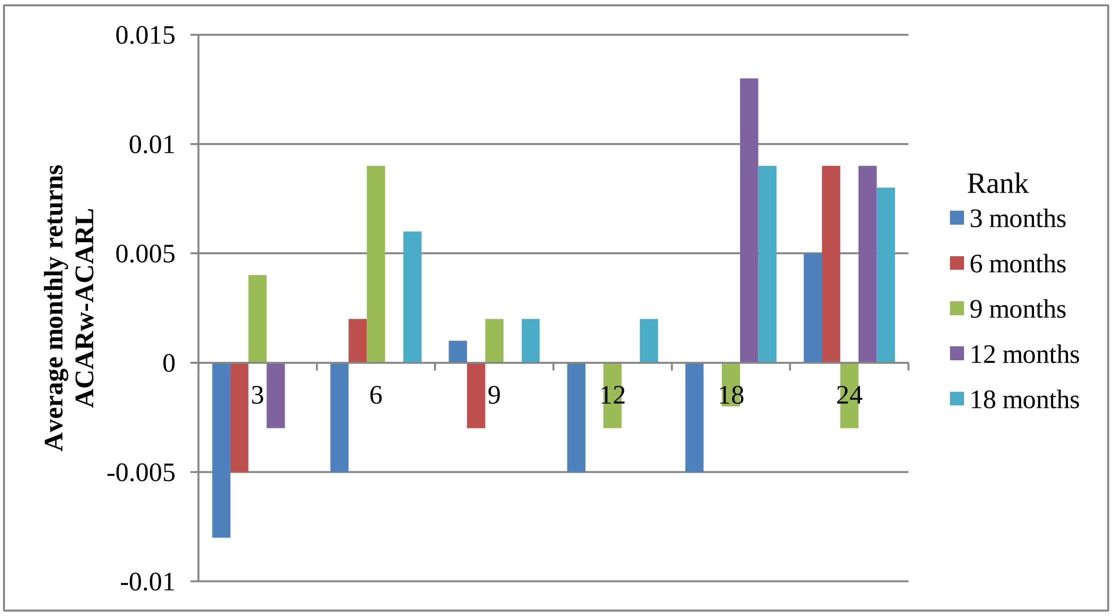


Table 5.8 presents the returns of the strength-rule strategy for industries during the Internet bubble period. The optimum strategy is 3/12 generating an average monthly return of 1.5 per cent, statistically significant at the 10 per cent level. This return is marginally less than the 1.7 per cent achieved in the overall time period, notably with the same length of rank/hold combination. The loser portfolio contributes 80 per cent of the recorded momentum return.

Table 5.8 Strength-rule strategy returns industries during the Internet bubble (1995 - 2002)

This table presents the average monthly returns of the strength-rule strategy for portfolios formed on the basis of industries for the sub-period 1995 to 2002. CAR_w-CAR_L returns are reported. The performance of winner and loser portfolios can be found in appendix E. T-statistics are reported in parenthesis and calculated using the method of De Bondt and Thaler (1985).

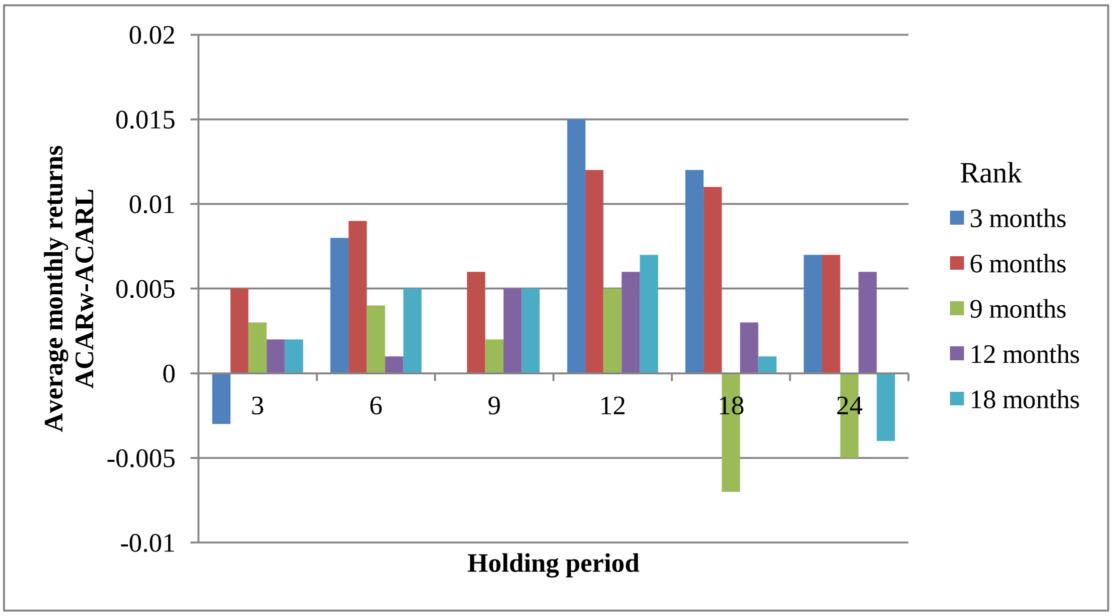
Rank/Hold period (months)	3	6	9	12	18	24
3	-0.003	0.008	0.000	0.015***	0.012	0.007
	(1.06)	(1.62)	(0.05)	(1.82)	(1.28)	(0.59)
6	0.005***	0.009**	0.006	0.012	0.011***	0.007
	(2.02)	(2.30)	(1.07)	(1.85)	(1.45)	(0.78)
9	0.003	0.004	0.002	0.005	-0.007	-0.005
	(1.26)	(1.19)	(0.43)	(0.90)	(1.06)	(0.64)
12	0.002	0.001	0.005	0.006	0.003	0.006
	(0.81)	(0.14)	(1.00)	(1.19)	(0.42)	(0.63)
18	0.002	0.005	0.005**	0.007**	0.001	-0.004
	(1.14)	(1.87)	(3.12)	(3.13)	(0.47)	(1.04)

*significant at 1% level
**significant at 5% level
***significant at 10% level

Figure 5.10 graphically presents the returns of the strength-rule for industries during the Internet bubble period. Evidence of partial reversal is evident after a period of 18 months is exceeded. The six-month ranking strategy performs comparably well during this period, achieving returns of 1.5 and 1.1 per cent for a 3/12 and 6/18 combination respectively. However, the highest Sharpe ratio of 1.56 is recorded during the 18/9 and 18/12 combinations which also generate positive monthly momentum return, but less than one per cent.

Figure 5.10 Returns to strength-rule strategies for industries for Internet bubble 1995-2002

Figure 5.10 presents the returns of the strength-rule strategy for industries during the years 1995-2002 for all rank and hold combinations.

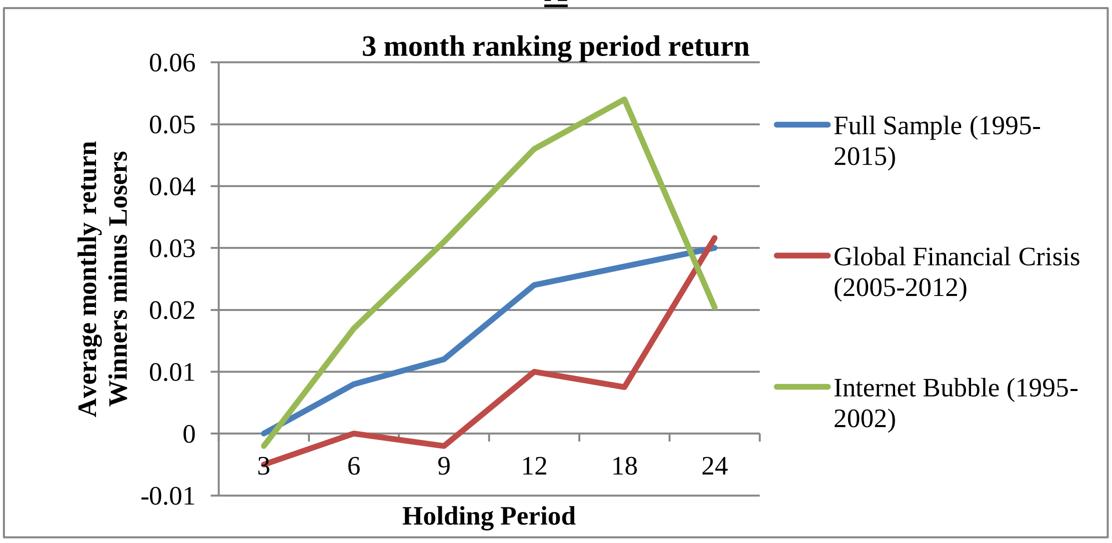


Figures 5.11 A to E compare the average monthly returns of the various rank periods for each of the three time frames of analyses, when portfolios consist of individual stocks. Each figure presents the performance of the five different rank periods separately.

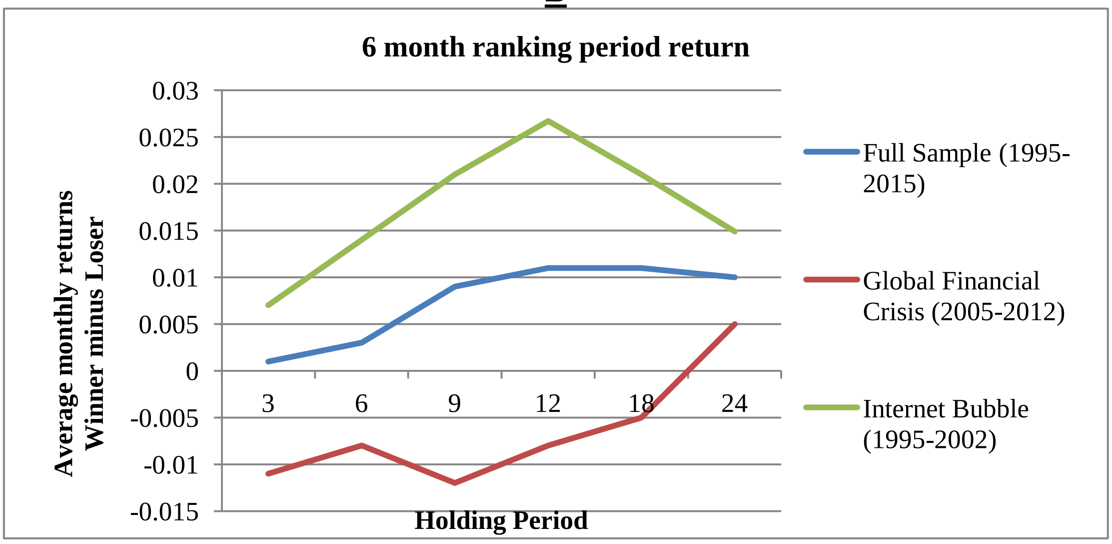
Figure 5.11 Returns to strength-rule strategy rank period comparisons

This figure compares the average monthly return of the strength-rule strategy (winner minus loser) for the overall time period, global financial crisis and Internet bubble sub-periods. Figure 5.11 A refers to the average monthly returns of a three-month rank period. B presents average monthly returns of a six-month rank period, and C, D and E present average monthly returns of nine, twelve and 18-month rank periods respectively. Portfolios are equally-weighted on the basis of individual stock performance and returns are calculated using the 3-factor Fama and French (1993) model in equation 4.4.

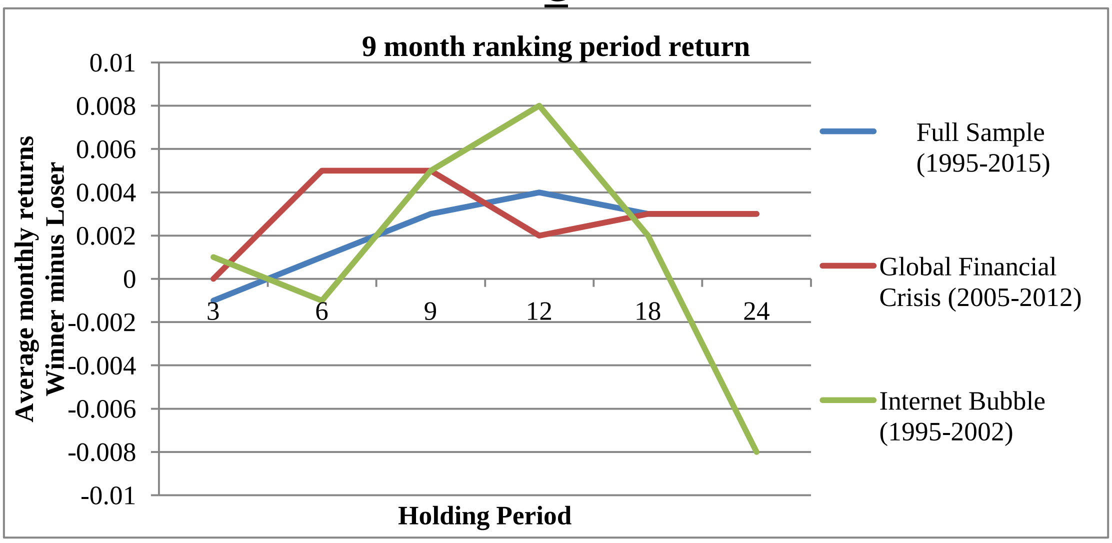
A



B

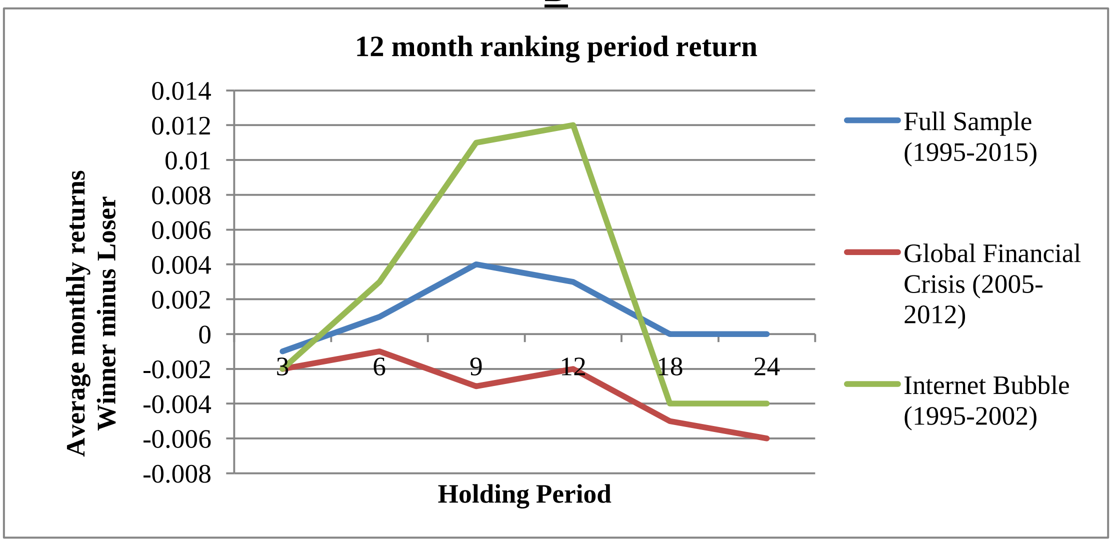


C



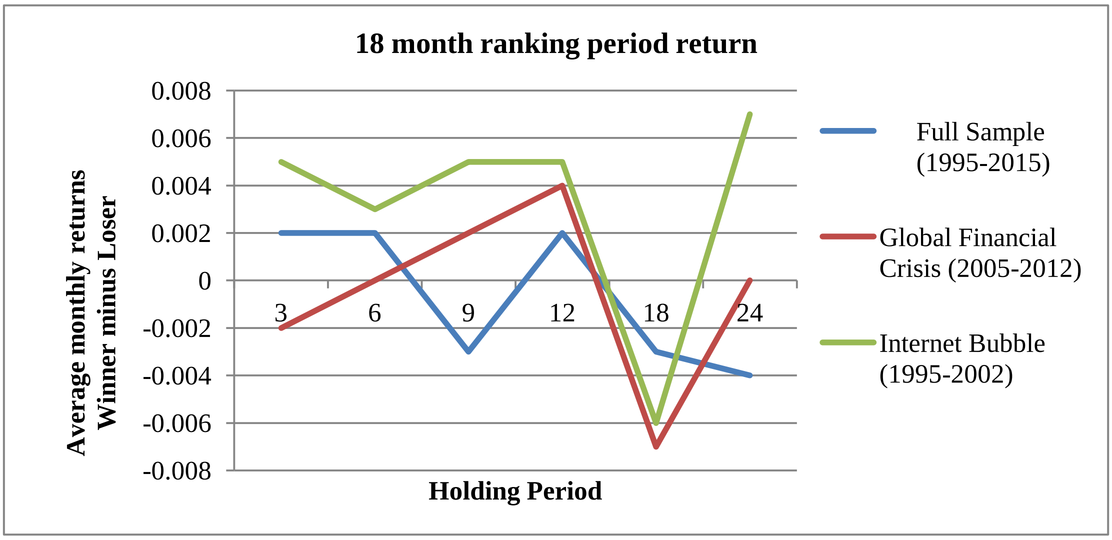
9 month ranking period return
Average monthly returns
Winner minus Loser
0.01
0.008
0.006
0.004
0.002
0
-0.002
-0.004
-0.006
-0.008
-0.01
3
6
9
12
18
24
Holding Period
Full Sample (1995-2015)
Global Financial Crisis (2005-2012)
Internet Bubble (1995-2002)

D



12 month ranking period return
Average monthly returns
Winner minus Loser
0.014
0.012
0.01
0.008
0.006
0.004
0.002
0
-0.002
-0.004
-0.006
-0.008
3
6
9
12
18
24
Holding Period
Full Sample (1995-2015)
Global Financial Crisis (2005-2012)
Internet Bubble (1995-2002)

E



It is evident from figure 5.11 A to E that the strength-rule strategy performed best on average during the Internet bubble period. Specifically, the three-month rank period performs best compared to all other ranking strategies during the Internet bubble period. Furthermore, during the overall time frame and global financial crisis period, the average monthly return continued to increase as the length of the holding period increased, unlike during the Internet bubble period when evidence of reversal is most apparent.

The six and twelve-month rank strategies fail to achieve positive returns during the global financial crisis period on any occasion, (figure 5.11 B and D), but do perform more consistently during the overall and Internet bubble time periods.

Finally, figure 5.11 E presents the average monthly returns of a momentum strategy with stocks ranked on the basis of returns during the previous 18 months. A sharp decline in average monthly returns is apparent in all three time periods of analysis after a period of 18 months; however, the return does recover after a period of 24 months.

5.4 Value of analysts' advice

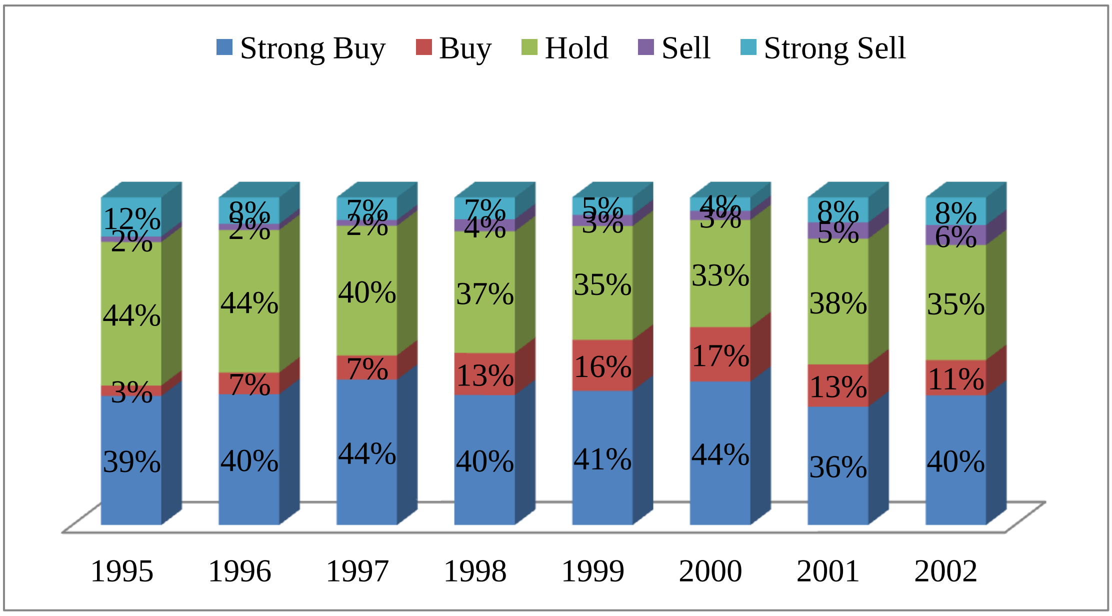
This section details the results of the methodology outlined in section 4.6 in relation to the behaviour and accuracy of analysts during the Internet bubble and global financial crisis. The frequency of recommendations and veracity of analysts' advice during these times of crises is presented. Section 5.4.1 details the frequency of each recommendation category issued by analysts to determine the level of optimism in analysts' recommendations. Section 5.4.2 deals with whether analysts' forecasts reinforce or contradict the recommendation revision issued by analysts and section 5.4.3 presents findings in relation to the accuracy of analysts' recommendations.

5.4.1 Frequency of recommendations

This section details the frequency of recommendations during the two crisis periods. It is generally accepted in the literature that an analyst's level of optimism can be measured by observing the frequency of recommendations in each category of recommendations issued; Barber *et al.* (2006) and Kadan *et al.* (2009) observed the level of optimism in analysts' recommendations by examining the frequency of buy recommendations issued. Figures 5.12 and 5.14 present the pattern of recommendations in each category during the two crisis periods for all sectors.

Figure 5.12 Frequency of recommendations by category 1995 to 2002

Figure 5.12 presents the frequency of recommendations issued across recommendation categories for all sectors between the years 1995 and 2002.



For all sectors between 1995 and 2002 *strong buy* recommendations are the most frequently issued recommendation on average; *hold* recommendations are more frequent in 1995 and 1996 and 2001. The other recommendation categories; *buy, sell* and *strong sell* are issued less frequently by a significant margin. In all years (1995 to 2002) *strong sell* recommendations are more frequently issued than the less extreme *sell* recommendation.

On average, the ratio of *buy-to-sell*[26] recommendations between 1995 and 2002 is 5:1, however it must be noted that this average figure is largely driven by a significantly high ratio of *buy-to-sell* recommendations in the year 2000; 8.8:1. In the years leading up to 2000, the ratio of *buy-to-sell* recommendations increased steadily. After the

[26] For the purposes of ratio calculations the *buy* calculation includes *strong buy* and *buy* recommendations and the *sell* calculation includes *strong sell* and *sell* recommendations.

Internet bubble implosion in April 2000, the ratio of *buy-to-sell* recommendations decreased in 2001 and 2002 to 3.9:1 and 3.5:1 respectively. Figure 5.13 diagrammatically presents the ratio of *buy-to-sell* recommendations.

Figure 5.13 Ratio of *buy-to-sell* recommendations 1995-2002

This figure depicts the ratio of *buy-to-sell* recommendations for all sectors between 1995 and 2002.

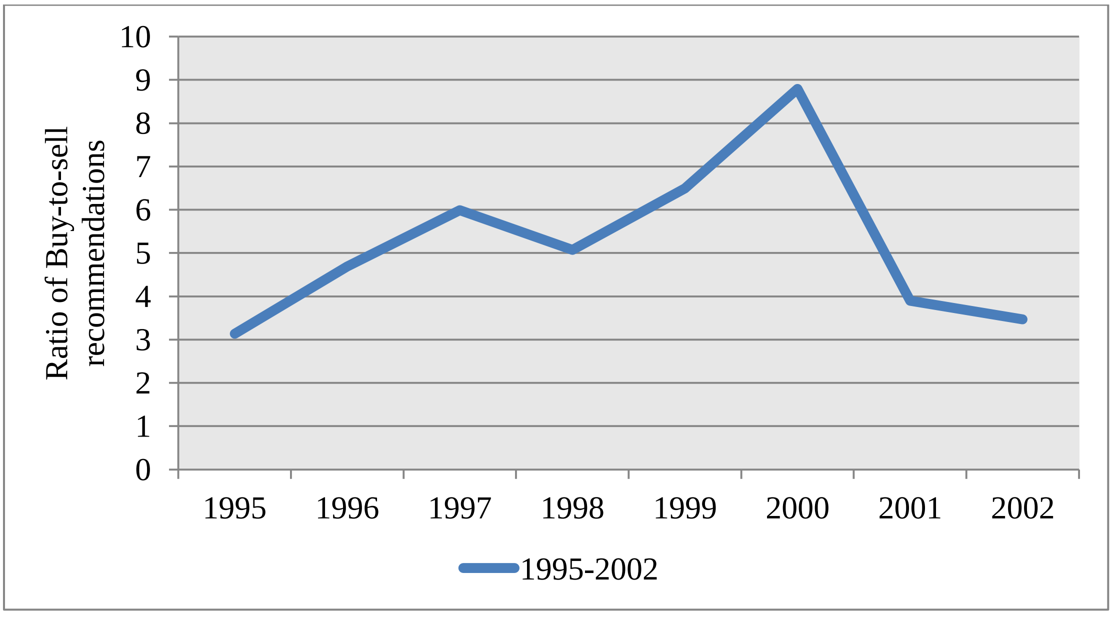
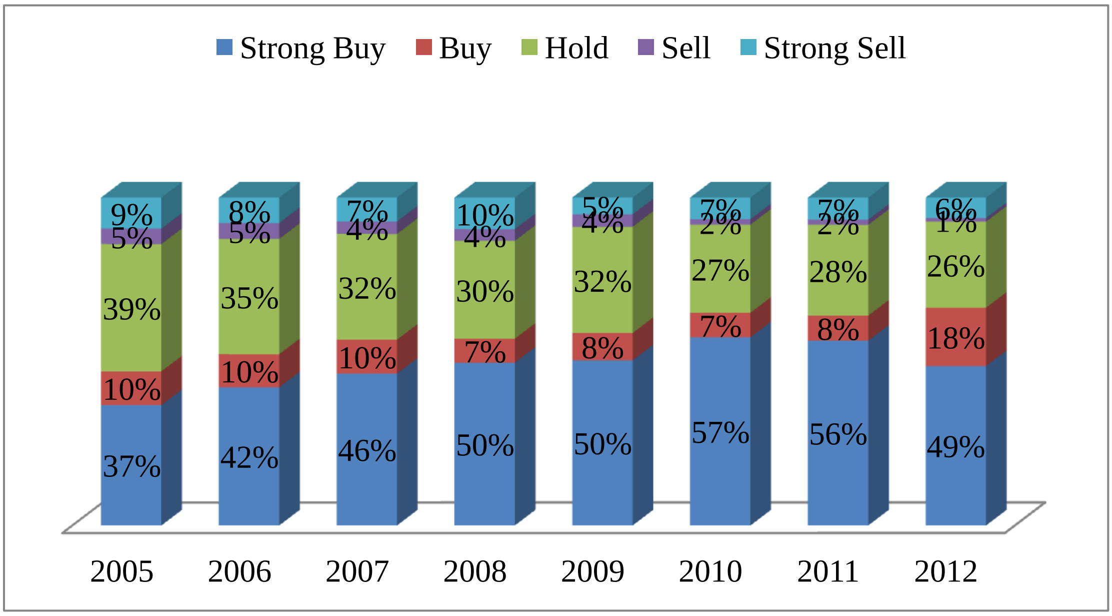


Figure 5.14 illustrates the frequency of recommendations across all recommendation categories for the financial crisis period years (2005-2012). The percentage of *buy, sell* and *strong sell* recommendations remain relatively stable throughout the sample time period with *buy* recommendations increasing marginally in 2012. Similar to the results presented in figure 5.12, *strong sell* recommendations are more frequently issued than the less extreme *sell* recommendation between 2005 and 2012. The frequency of *strong buy* and *hold* recommendations mimic one another in pattern, with an increase in the number of *strong buy* and *hold* recommendations in 2009 before decreasing steadily in

the following years. The *strong buy* recommendation is the most frequently issued recommendation between 2005 and 2012 and is perceived to be a positive recommendation.

Figure 5.14 Frequency of recommendations by category 2005 to 2012

Figure 5.14 presents the frequency of recommendation per category for all sectors between 2005 and 2012.



The ratio of *buy-to-sell* recommendations during the years 2005 to 2012 for all sectors is illustrated in figure 5.15. An upward trend in the ratio of *buy-to-sell* recommendations is apparent for recommendations across all sectors between 2005 and 2012. The lowest ratio of *buy-to-sell* is observed in 2005; 3.3:1, and the highest ratio recorded in 2010: 7.:1. The average ratio of *buy-to-sell* recommendations between 2005 and 2012 is 5.3:1. Figure 5.15 presents the ratio of *buy-to-sell* recommendations across all sectors between 2005 and 2012.

Figure 5.15 Ratio of *buy-to-sell* recommendations 2005-2012

This figure depicts the ratio of *buy-to-sell* recommendations across all sectors between 2005 and 2012.

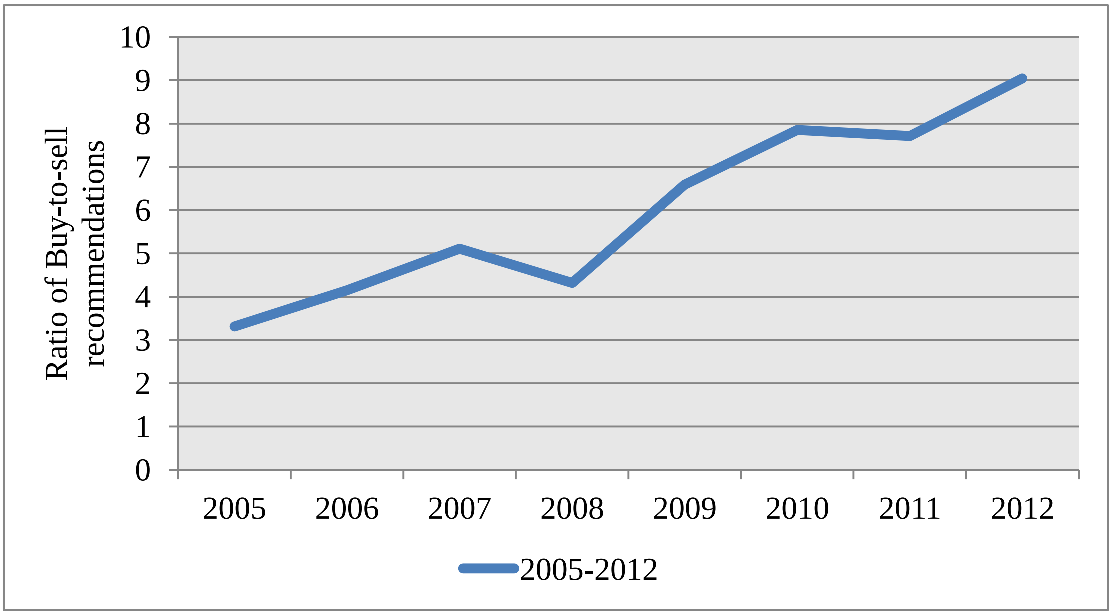


Figure 5.16 illustrates the number of recommendations issued per recommendation category for the years 1995 to 2002 for stocks in the TTM sector. The most frequently issued recommendation is generally *strong buy* with the notable exception in the year 2001 when the frequency of *hold* recommendations surpass the *strong buy* category. The *sell* recommendation is the least frequently issued recommendation in all years.

Figure 5.16 Frequency of recommendation in each category for stocks in the TTM sector for the period 1995 to 2002

This figure illustrates the number of recommendations in each category, *strong buy*, *buy*, *hold*, *sell* and *strong sell* for stocks in the TTM sector between 1995 and 2002.

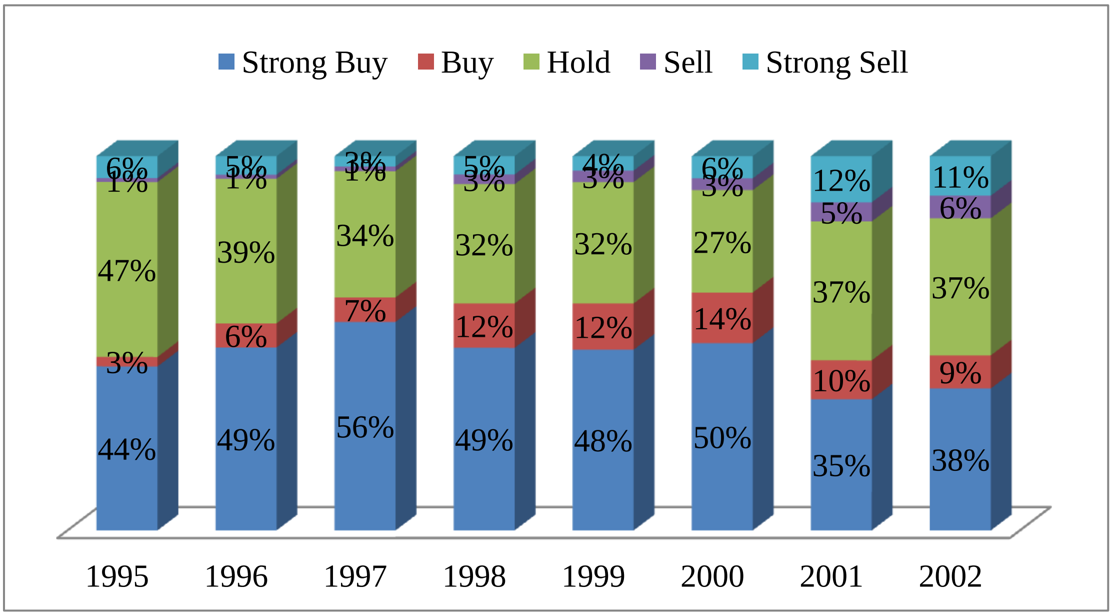


Figure 5.17 illustrates the ratio of *buy-to-sell* recommendations in the TTM sector between 1995 and 2002. The average ratio of *buy-to-sell* recommendations in the TTM sector between 1995 and 2002 is 5.2:1. Interestingly, the highest ratio of *buy-to-sell* recommendations is observed in 1997 (15:1). The ratio of *buy-to-sell* recommendations exhibits a downward trend from 1997 onwards, with the lowest ratio of 2.6:1 observed in 2001.

Figure 5.17 Ratio of *buy-to-sell* recommendations in the TTM sector 1995-2002

This figure depicts the ratio of *buy-to-sell* recommendations issued by analysts in the TTM sector for the years 1995-2002.

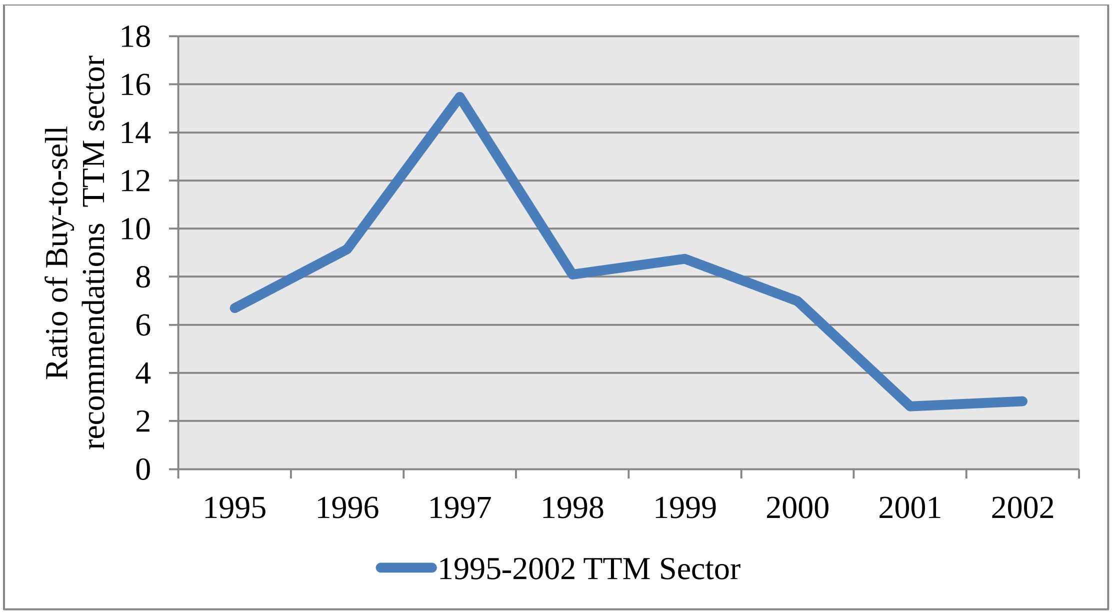


Figure 5.18 illustrates the frequency of recommendations in each category for stocks in the BFI sector between 2005 and 2012, the global financial crisis years. *Hold* recommendations outnumber other categories of recommendations in 2005, 2006 and 2007. From 2008 onwards *strong buy* recommendations are the most frequently issued, accounting for over 50 per cent of all recommendations in the years 2010 and 2011, furthermore, *strong sell* recommendations are issued more frequently than the less extreme *sell* recommendation in all years during the global financial crisis period.

Figure 5.18 Frequency of recommendation in each category for stocks in the BFI sector for the period 2005 to 2012

This figure illustrates the number of recommendations in each category, *strong buy, buy, hold, sell* and *strong sell* for stocks in the BFI sector between 2005 and 2012.

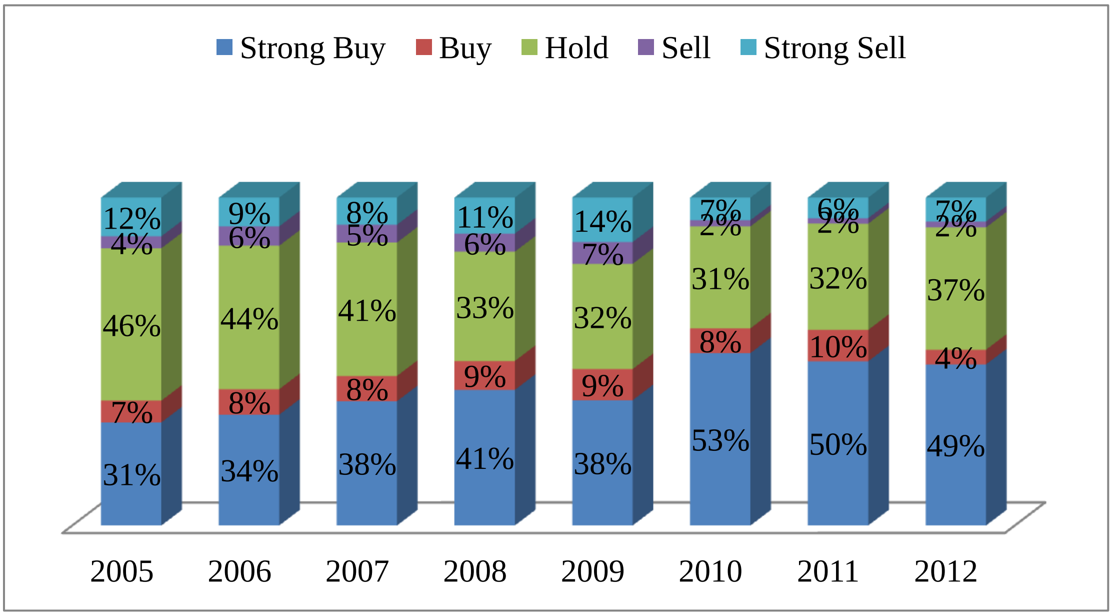
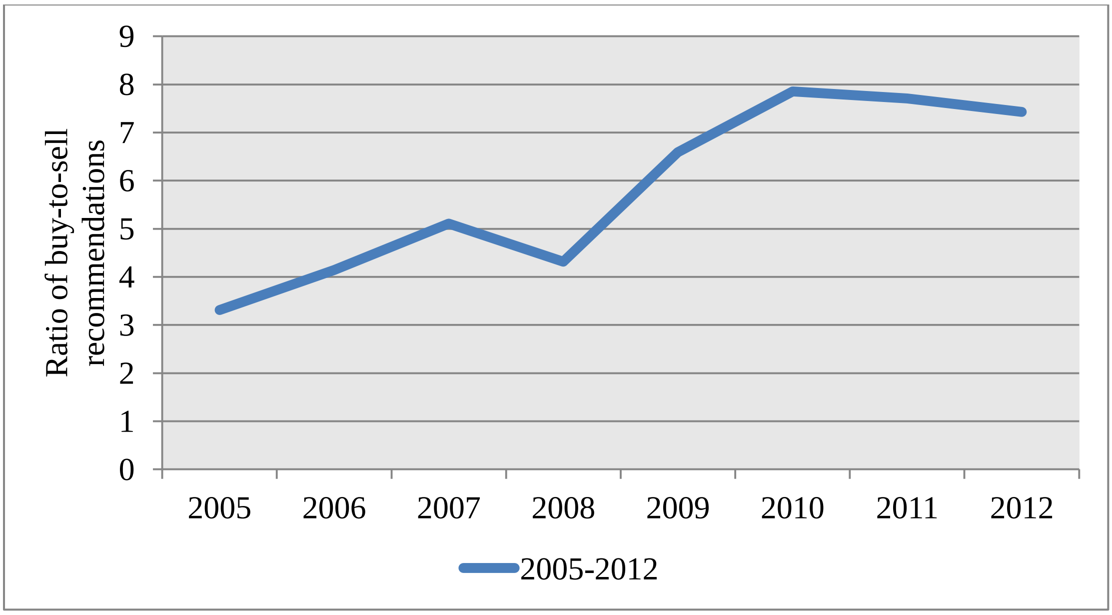


Figure 5.19 illustrates the ratio of *buy-to-sell* recommendations for BFI sector stocks between 2005 and 2012.The average ratio of *buy-to-sell* recommendations is 3.4:1 for stocks in the BFI sector between 2005 and 2012. The lowest ratio of *buy-to-sell* recommendations is observed in 2009; 2.3:1, the highest ratio of *buy-to-sell* recommendations is observed in 2011; 7.5:1.

Figure 5.19 Ratio of *buy-to-sell* recommendations in the BFI sector 2005-2012

This figure depicts the ratio of *buy-to-sell* recommendations issued by analysts in the BFI sector for the years 2005-2012



5.4.2 Reinforcement of analysts' recommendations

It is determined if earnings forecast revisions reinforce or contradict the signal sent by analysts' recommendations, i.e. that if in the presence of a negative recommendation analysts tend to issue more favourable earnings forecasts, an issue highlighted by Francis and Philbrick (1993). This is achieved by scaling monthly average earnings forecasts revisions by price for each stock in both the TTM and BFI sectors, during relevant financial crisis periods.

Figure 5.20, A and B, illustrate the average revision of earnings forecasts for stocks in the TTM sector pre and post April 2000. The average revision of forecasts is relatively small for each recommendation category both prior to April 2000 and after the Internet bubble burst. For TTM stocks prior to the Internet crash (1995 to April 2000), the average upward revision of earnings forecasts in the *strong buy* category exceeds the earnings forecast revision in the *strong sell* category. After the Internet bubble burst in April 2000, the largest downward revision is observed in the *strong sell* recommendation category, albeit relatively small at one thousandth of a penny.

Figure 5.20 A and B Analyst recommendation revision TTM sector

Presented in Figure 5.20 A and B are the mean earnings forecast revision (scaled by price) for stocks in the TTM sector across the five recommendation categories. Figure 5.20 A presents the results before the Internet bubble burst (pre April 2000) and figure 5.20 B presents the results after the Internet bubble burst (April 2000 to 2002).

A **B**

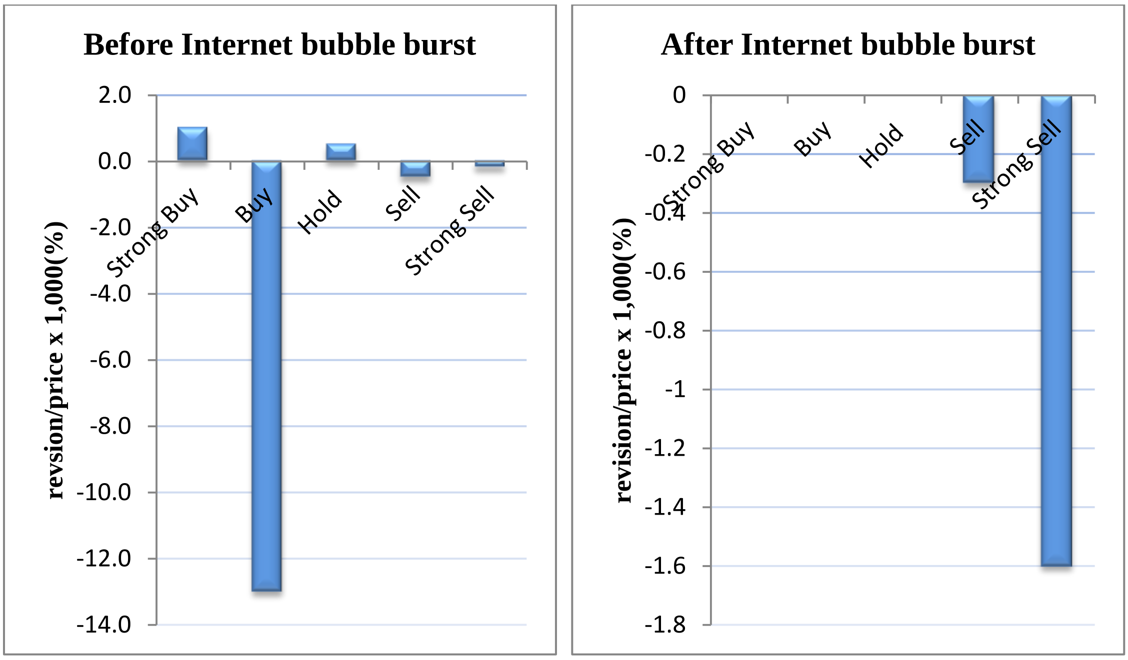


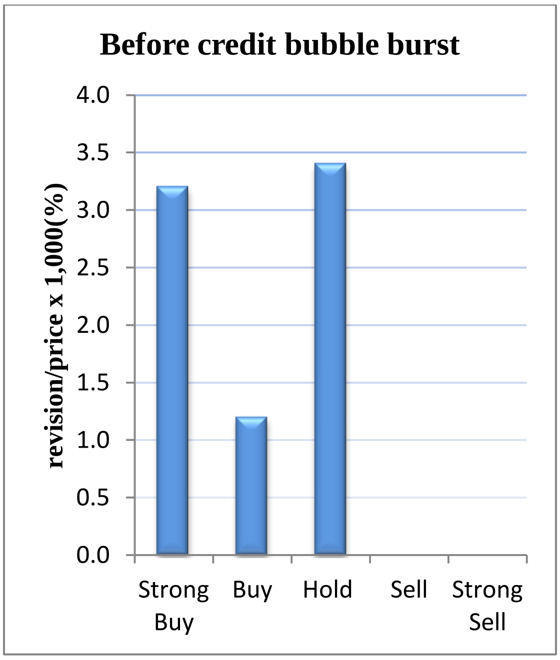
Figure 5.21 A and B present the monthly average earnings forecast revisions scaled by price for stocks in the BFI sector prior to and after September 2007. For BFI stocks prior to September 2007 the largest monthly average forecast revision is observed for the *hold* category; similar to stocks in the TTM sector, the earnings forecast revision is relatively small at below a thousandth of a penny on average. No earnings forecasts

revisions are recorded for stocks in the *sell* and *strong sell* categories for stocks in the BFI sector prior to September 2007. After the credit crisis of September 2007 (Figure 5.21 B) downwards revisions of earnings forecasts are observed for the *hold*, *buy* and *strong buy* categories.

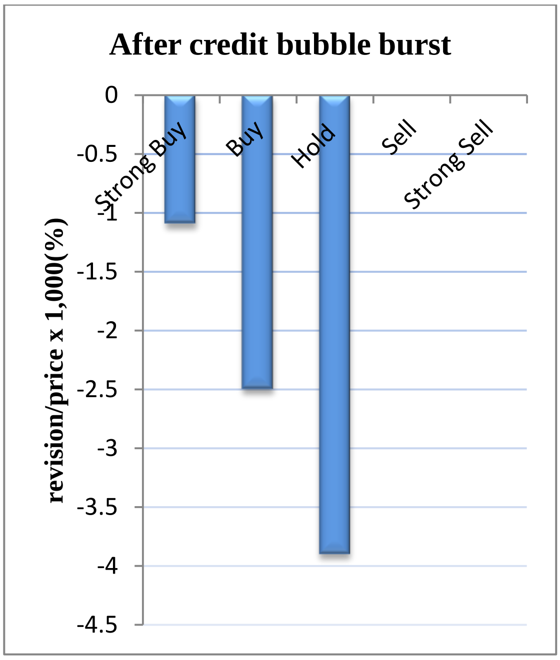
Figure 5.21 A and B Analyst recommendation revision BFI sector

Presented in Figure 5.21 A and B are the mean earnings forecast revision (scaled by price) for stocks in the BFI sector across the five recommendation categories. Figure 5.21 A presents the results before the credit bubble burst (pre September 2007) and figure 5.21 B presents the results after the credit bubble burst (September 2007 to 2012).

A



B



5.4.3 Accuracy of analysts' recommendations

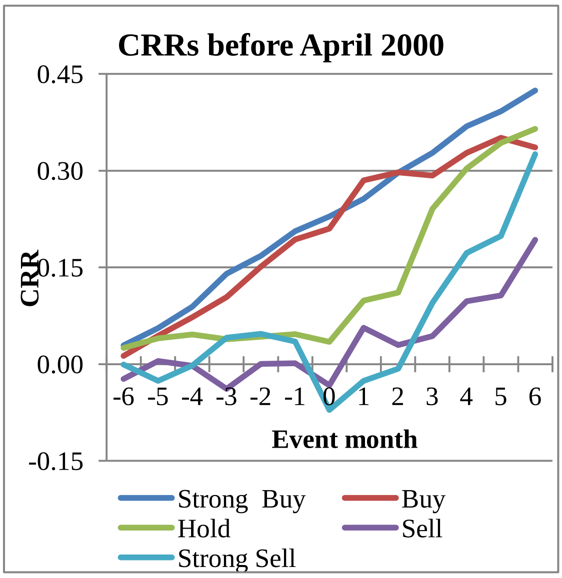
The veracity of analysts' recommendations are detailed in this section. Presented are the returns as a consequence of following analysts' advice, i.e. implementing a strategy whereby a long position is taken in the *strong buy* category and a short position is taken in the *strong sell* category. The raw returns and risk-adjusted returns of all recommendation categories over a 13-month event window for stocks in the TTM and BFI sectors are presented. A distinction is made between before and after the Internet bubble collapse and the credit crisis.

The CRRs and CARs of stocks for analyst recommendation categories during the 13-month event window around the recommendation issue date for stocks in the TTM sector are illustrated in figure 5.22 A to D. The CRRs of TTM stocks during the period prior to April 2000, are illustrated in figure 5.22 A; *strong buy* and *buy* categories exhibit a strong upward trend preceding and following the recommendation issue date in the years before the Internet bubble burst. A clear divergence between the two most extreme recommendations (*strong buy* and *strong sell*) is evident in the months prior to the recommendation issue date.

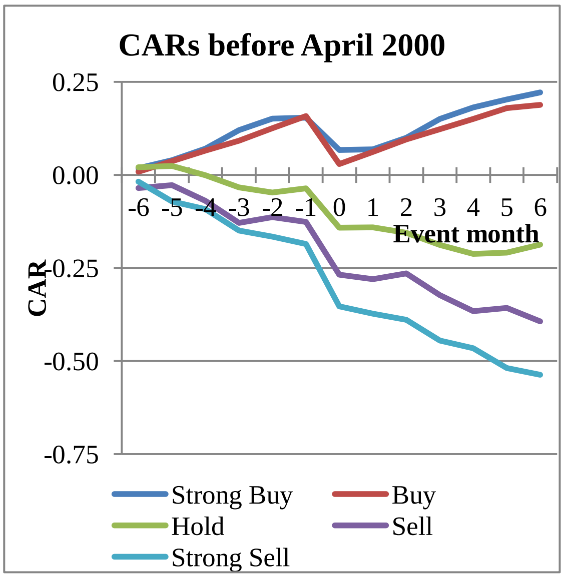
Figure 5.22 CRRs and CARs across recommendation categories for stocks in the TTM sector

Figure 5.22 A-D presents the cumulative raw returns (CRRs) and cumulative abnormal returns (CARs) of stocks in the TTM sector across recommendation categories over a 13-month event window relative to recommendation date, before and after the Internet bubble burst (April 2000).

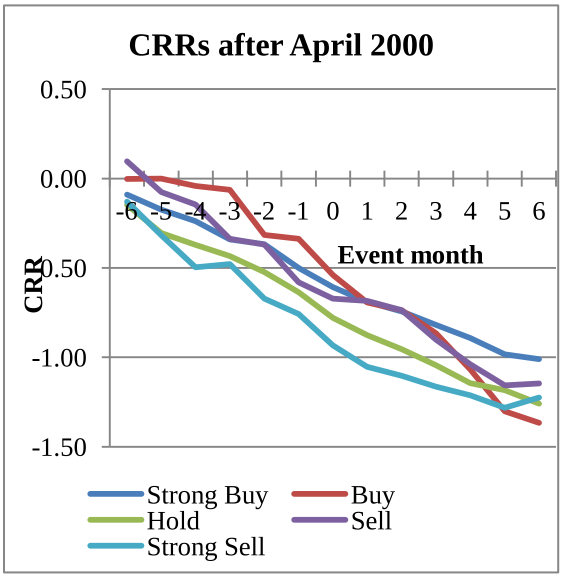
A



B



C



D

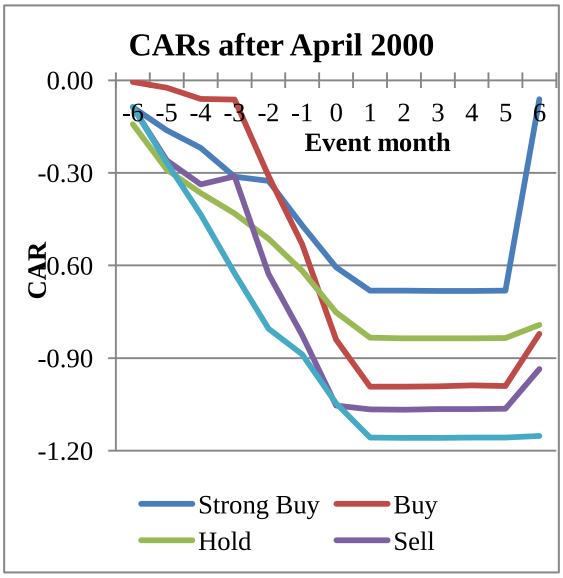


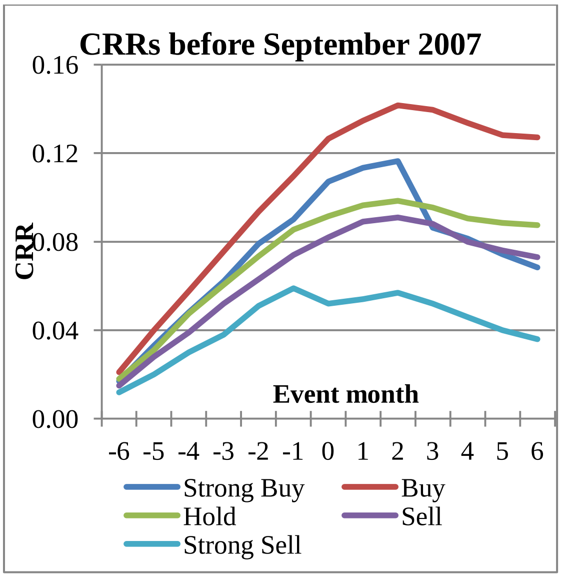
Table 5.9 Panel A presents the difference between the CRRs and CARs of the most extreme recommendations (*strong buy* and *strong* sell) over the 13-month event window relative to month *t.* The difference in the CRRs between *strong buy* and *strong sell* recommendations is positive, but insignificant, in the six months prior to *t*, in the six months after *t* the difference is positive and significant. The difference in CARs after the bubble burst is significant and positive. Figure 5.22 B presents the CARs of TTM stocks prior to April 2000 and the results are qualitatively similar implying the FF3F model does not capture the potential risk in the CRRs.

Figure 5.22 C presents the CRRs of stocks in the TTM sector across analyst recommendation categories after the Internet bubble burst (post April 2000). The performance across all recommendation categories is relatively poor from April 2000 to December 2002. In the six months prior to the recommendation issue date, *buy* recommendations outperform other categories. In the six months post recommendation date, *strong buy* recommendations outperform all other recommendation categories. Analysing the return generated in the 13-month event window relative to recommendation month for a long-short strategy, pre and post crisis period; the average CRR across all 13 months for the TTM sector pre-Internet crash is 0.1964 increasing to 0.2591 after April 2000. The cumulative abnormal return (CAR) average across the 13-month event window for the TTM sector pre-April 2000 is 0.4082 increasing marginally to 0.4184 after April 2000.

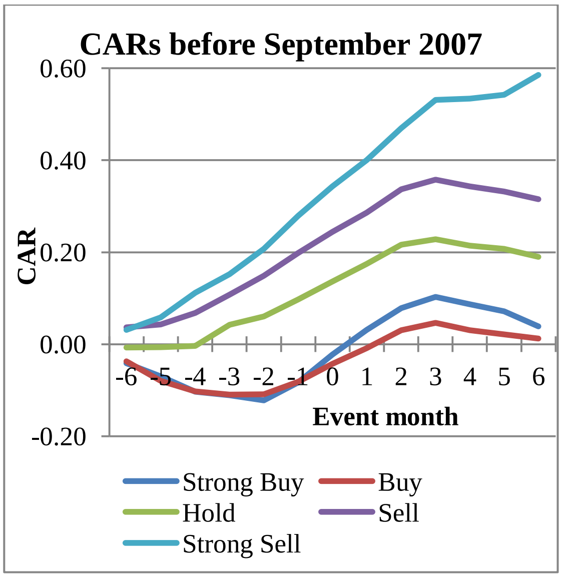
Figure 5.23 CRRs and CARs across recommendation categories for stocks in the BFI sector

Figure 5.23 A-D presents the cumulative raw returns (CRRs) and cumulative abnormal returns (CARs) of stocks in the BFI sector across recommendation categories over a 13-month event window relative to the recommendation date, before and after the credit bubble burst (September 2007).

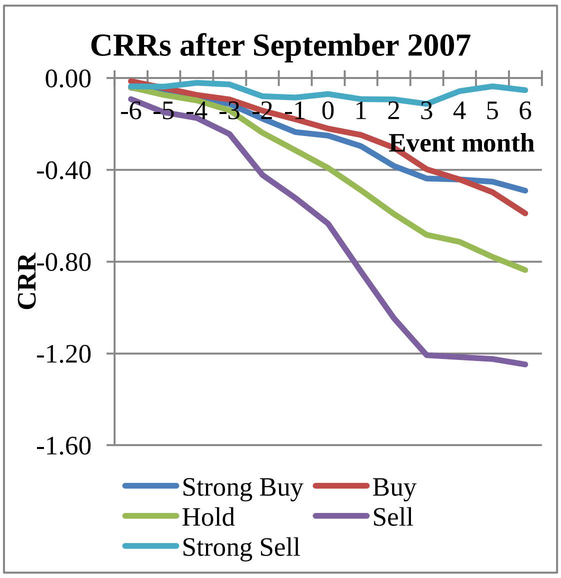
A



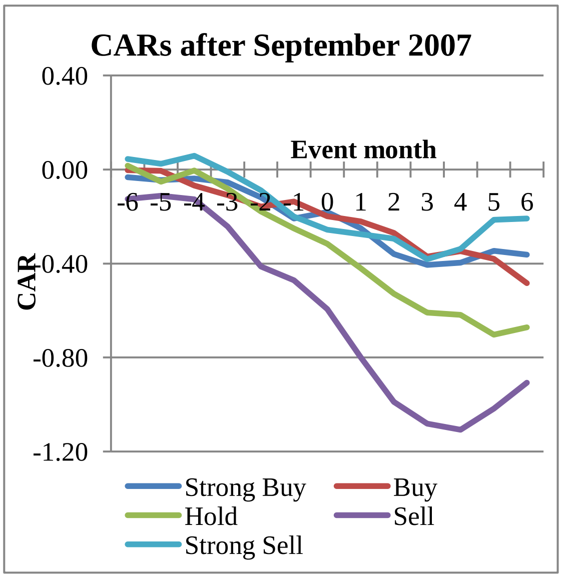
B



C



D



The CRRs and CARs of stocks in the BFI sector for the 13-month event window relative to the recommendation date, are presented in figures 5.23 A to D. Specifically, figure 5.23 A and B present the CRRs and CARs of a 13-month event window prior to the credit crisis period of September 2007. All recommendation categories exhibit an upward trend in the six months prior to the recommendation issue date; however, in the six months after the recommendation issue date, any upward gain is eroded. When returns are adjusted by the FF3F model (Figure 5.23 B) the returns to the *strong sell* category outperforms all other categories.

Table 5.9 Panel B presents the returns generated from a long/short strategy on the basis of analysts' advice; it is evident that a significant return can be generated from a long/short strategy if the signal of analysts' advice is inverted in the period prior to the credit crisis. The average CRR across the 13-month event window for the BFI sector pre-credit crisis is 0.0327, after the credit crisis period of September 2007; this average drops to -0.2096. The average CAR for a long/short strategy in the BFI sector across the 13-month event window increases from -0.3373 pre-September 2007 to -0.0491 post-September 2007.

Table 5.9 Difference in CRRs and CARs for extreme recommendation categories

This table presents the difference in the CRRs and CARs for stocks in the extreme recommendation categories (*strong buy* and *strong sell*) over a 13-month event window relative to recommendation month. The results relating to the TTM sector are displayed in Panel A and the results relating to the BFI sector displayed in Panel B. Results of both before and after the crisis periods are presented. The CARs are adjusted by the Fama-French Three factor model as seen in equation 4.4. T-statistics are reported in parentheses.

	Before the Internet/credit bubble burst				**After the Internet/credit bubble burst**			
	Difference of CRRs		**Difference of CARs**		**Difference of CRRs**		**Difference of CARs**	
Event Month	*Mean*	*t-stat*	*Mean*	*t-stat*	*Mean*	*t-stat*	*Mean*	*t-stat*
Panel A: TTM Sector								
-6	0.0298	(0.63)	0.0362	(0.98)	0.0385	(0.77)	-0.001	(0.97)
-5	0.0820	(1.45)	0.1102	(1.88)***	0.1438	(1.61)	0.1052	(1.88)***
-4	0.0910	(0.99)	0.1620	(3.19)*	0.2575	(2.92)*	0.2160	(3.20)*
-3	0.0991	(1.56)	0.2704	(3.69)*	0.1379	(3.34)*	0.3139	(3.69)*
-2	0.1210	(1.64)	0.3172	(4.74)*	0.3053	(4.46)*	0.4789	(4.740*
-1	0.1711	(1.53)	0.3393	(3.88)*	0.2580	(3.68)*	0.4180	(3.88)*
0	0.3003	(2.94)*	0.4196	(3.41)*	0.3244	(3.85)*	0.4398	(3.42)*
1	0.2823	(2.89)*	0.4417	(3.42)*	0.3628	(3.84)*	0.4763	(3.42)*
2	0.3042	(3.65)*	0.4885	(3.42)*	0.3598	(3.61)*	0.4761	(3.42)*
3	0.2844	(2.66)*	0.5947	(3.42)*	0.3470	(3.48)*	0.4763	(3.42)*
4	0.2715	(2.12)**	0.6465	(3.42)*	0.3217	(3.09)*	0.4756	(3.42)*
5	0.2855	(2.41)**	0.7223	(3.41)*	0.2979	(2.86)*	0.4752	(3.41)*
6	0.2313	(1.55)	0.7585	(3.93)*	0.2137	(3.01)*	1.0900	(3.93)*
Panel B: BFI Sector								
-6	0.0050	(0.79)	-0.072	(8.51)*	-0.006	(-0.75)	-0.079	(-9.43)*
-5	0.0130	(1.63)	-0.128	(10.25)*	-0.029	(0.26)	-0.070	(-5.75)*
-4	0.0181	(-2.04)**	-0.215	(9.66)*	-0.064	(0.50)	-0.097	(-5.69)*
-3	0.0241	(-2.03)**	-0.263	(8.21)*	-0.086	(0.23)	-0.044	(-1.51)
-2	0.0281	(0.75)	-0.329	(6.54)*	-0.0980	(0.19)	-0.029	(-1.61)
-1	0.0311	(-1.08)	-0.362	(6.54)*	-0.150	(1.42)	-0.008	(-0.40)
0	0.0551	(-1.76)**	-0.365	(1.50)	-0.182	(2.52)**	0.075	(1.56)
1	0.0551	(-1.90)**	-0.369	(-0.02)	-0.206	(2.78)*	0.026	(0.08)
2	0.0594	(-2.47)**	-0.391	(2.24)**	-0.290	(2.21)**	-0.065	(-1.71)**
3	0.0344	(-2.24)**	-0.428	(-4.03)*	-0.326	(2.66)*	-0.025	(-1.04)
4	0.0354	(-2.18)*	-0.447	(-1.91)***	-0.385	(3.42)*	-0.057	(-1.37)
5	0.0344	(-2.62)*	-0.470	(0.69)	-0.4155	(3.81)*	-0.131	(-2.24)**
6	0.0324	(-2.88)*	-0.546	(0.19)	-0.4369	(3.83)*	-0.154	(-2.76)*

*significant at the 1% level

**significant at the 5% level
***significant at the 10% level

After September 2007 negative CRRs are observed for all recommendation categories (Figure 5.23 C), with *strong sell* outperforming other categories and remaining relatively consistent over the 13-month event window. The performance of the *strong sell* category in comparison to the *strong buy* category implies that, in a similar tactic implemented before the credit crisis, the practice of inverting analysts' signals generates significant returns after September 2007. Table 5.9 Panel B illustrates the aforementioned results. Furthermore, when returns are adjusted for risk, profits are diminished but still attainable in the fifth and sixth month after recommendation issue date.

Estimating the partial adjustment model of equation 4.9, it is found that analysts' advice has no significant impact on monthly returns at the aggregate level. A downward revision from a *strong buy* to a *buy*, denoted by the change in rating ($\Delta Rating$), is positively but insignificantly related to returns in both the TTM and BFI sector. Similarly, insignificant coefficients are found for the lagged earnings forecast error scaled by price ($\frac{ME_{t-1}}{P_t}$) and the earnings forecast revision scaled by price ($\frac{\Delta MF_t}{P_t}$). The results of equation 4.9, presented in table 5.10, show that no stable significant relationship exists between stock returns and metrics used to measure analysts' advice at the aggregate level.

Table 5.10 Regression of monthly stock returns on analysts' advice

Table 5.10 presents the results of the regression of monthly average stock returns on monthly averages of analysts' advice. Measures of analysts' advice include earnings forecasts and recommendations. The explanatory variables used in this calculation are explained by equation 4.9. *T*-statistics are reported in parentheses. Panels A and B presents results pertaining to the TTM and BFI sectors respectively.

	Panel A Internet bubble period 1995-2002	**Panel B** Credit crisis period 2005-2012
Constant	-0.136 (-0.64)	0.049 (1.02)
$\frac{ME_{t-1}}{P_t}$	-0.892 (-0.45)	0.002 (1.50)
$\frac{MF_t}{P_t}$	0.634 (0.07)	-0.000 (-1.06)
$\frac{\Delta MF_t}{P_t}$	0.015 (0.58)	0.000 (0.38)
$Rating_t$	0.034 (0.08)	-0.015 (-1.00)
$\Delta Rating_t$	-0.073 (-0.89)	0.008 (0.76)
DUM_t	-0.013 (-1.26)	-0.013 (-0.84)
$Adjusted\ R^2$	0.047	0.096

5.5 Chapter Summary

Chapter five outlines the key results of this study pertaining to the performance of the momentum strategy and the value of analysts' recommendations. The return of the strength-rule strategies (momentum return) are documented for the overall time period, the Internet bubble period and the global financial crisis period. Furthermore, the results of industry momentum strategies are documented.

The momentum strategy is found to be profitable in the UK market between 1995 and 2015, with an observed average monthly return of 3.1 per cent. The presence of a month's gap between the rank and hold periods does appear to alter the returns materially. The highest average monthly returns of 5.4 per cent are recorded during the Internet bubble period and a return of 3.2 per cent is observed during the global financial crisis period, albeit this figure is predominantly driven by the performance of the 3/24 strategy. In general the optimal investment strategy consists of a short rank and long holding period.

The results of industry momentum are also detailed; industry momentum does not perform as consistently well as individual momentum strategies in all time periods of analysis. A return of 1.5 per cent is observed for the overall time period and during the Internet bubble years. During the global financial crisis period the industry return does not exceed 1 per cent on any occasion.

With regards to analysts' advice, it is noted that *strong buy* and *buy* recommendations are the most frequently issued recommendations during the Internet bubble and global financial crisis periods. The ratio of *buy-to-sell* recommendations varies year on year. Additionally, the revision of analysts' forecasts is small for each recommendation category at below one-thousandth of a penny for both TTM and BFI sectors.

The implementation of a long/short strategy on the basis of analysts' advice is profitable in the TTM sector both before and after April 2000. However, in the BFI sector implementing a long/short strategy on the basis of analysts' advice does not produce a significant return.

On an aggregate level, analysts' advice does not appear to contain investment value, as no significant relationship is found between average monthly stock returns and the various measures of analysts' advice in either the TTM or BFI sectors.

Chapter Six – Discussion

6.1 introduction

Chapter six includes the discussion of the key findings presented in chapter five. The discussion aims to answer the research objectives of this study as previously outlined in chapter one. Primarily, this chapter will discuss the main results of this study and compare these results to relevant prior studies. Potential causes of any identified trends or behaviours are also discussed. Section 6.2 includes discussion of the key momentum findings; section 6.3 addresses evidence of optimism in analysts' recommendations and section 6.4 reflects on the performance of analysts' recommendations during times of economic crisis and thus the potential value of analysts' recommendations to investors.

6.2 Momentum

According to prior literature momentum is possibly one of the most consistent anomalies in international stock markets. It is so persistent that the founder of the Efficient Market Hypothesis (EMH), Eugene Fama, could not explain the phenomena with rational causes (Fama, 1998). Overall, this study finds that momentum is present in the UK stock market between 1995 and 2015 and in general application of the strength-rule strategy generates abnormal returns.

6.2.1 Individual momentum

The optimum strategy of a three-month rank and 24 month hold period generates a monthly average return of 3.1 per cent (annualised 44 per cent); this return is significantly larger than the average monthly return of 1.31 per cent reported in the seminal study by Jegadeesh and Titman (1993) for the US. Rouwenhorst (1998) reported a similar figure of 1.35 per cent for a European wide average. The annualised return of 44 per cent is also significantly larger than the 16 per cent annualised return reported by Hon and Tonks (2003) for the UK market, albeit for the earlier years of 1955 to 1996.

The optimal strategy consisting of a short rank and long hold period contradict the findings of Jegadeesh and Titman (1993) and Rouwenhorst (1998) in a study of international markets, who find that a long rank period and shorter hold period combine to make the optimal strength-rule strategy. Furthermore, they report that in general momentum returns tend to increase as the ranking period lengthens; Hon and Tonks (2003) report similar evidence for the UK market. However, evidence in this study does not support this assertion and generally as the rank period increases in length the return declines. Similarly, Hu and Chen (2011) observe in a study of 48 international indices, that momentum is most profitable in a combination of a one or three-month rank period and nine-month holding period.

Momentum returns did not differ materially when a month's lag was present between the end of the rank period and the beginning of the formation period. However, Novy-Marx (2012) reports that it is the length of time between the rank and holding period which impacts most significantly on momentum return; observing the momentum strategies based on a ranking period twelve to seven months prior to portfolio formation as most optimal. Furthermore, the bid-ask spread for stocks listed on the FTSE100 may not be as significant an issue.

The length of the hold period can have major implications on the level of transaction costs incurred and a hold period in excess of six months is superior as it reduces the frequency of portfolio re-adjustment, therefore, as reported by Siganos (2010) and

Agyei-Ampomah (2007) the length of the hold period plays a significant role in determining the level of returns.

In contrast to the findings of Jegadeesh and Titman (1993) and Rouwenhorst (1998), the winner portfolios do not produce a positive abnormal return for all rank and hold combinations in this study; when the rank period exceeds nine months in length the loser portfolio begins to outperform the winner portfolio. Both the winner and loser portfolios perform best when a three-month rank period is selected. Furthermore, the purchasing of winner portfolios alone would generate returns in 70 per cent of the rank/hold combinations; an important aspect given the short-sale constraints that may be present during certain turbulent times in the market. Hong *et al.* (2000) in contrast, report that the selling of loser portfolios contributes to the majority of returns to the momentum strategy. Conversely, Clare and Thomas (1995) find evidence of winner portfolios outperforming loser portfolios in their study of momentum in the UK market. Novy-Marx (2012) shows evidence that winner and loser portfolios contribute evenly to momentum return.

Portfolios ranked for a period of three months fail to show evidence of reversal, differing from the findings of De Bondt and Thaler (1985) for US markets and Yi-Yu (2011) who find that momentum reverses after a period of one year. However, evidence of reversal is present in the six, nine, twelve and 18 month rank periods; similar to the evidence of Hu and Chen (2011) who state that longer rank periods reverse over a period of one-year and short rank periods reverse over a two-year period. Bhojraj and Swaminathan (2006) also report similar evidence of momentum reversal in international markets after a period of 24 months.

In their study of the UK market Hon and Tonks (2003) conclude that the overall momentum observed between 1955 and 1996 is primarily driven by momentum in the latter half of their sample. Evidence of significantly higher momentum returns in the

Internet bubble years of this study reaffirm this finding, implying momentum is an increasing trend in the later 1990s. The optimum strategy during the Internet bubble period continues to consist of a short rank and long holding period, with the winners and losers contributing evenly to the momentum return, again in contrast to Hong *et al.* (2000), a US study.

During the global financial crisis the momentum strategy, although still generating returns, did not do so at the level observed during the earlier time frame, this finding concurs with that of Galariotis *et al.* (2007) who show that momentum is in decline in the UK in the millennia years. The 3.2 per cent average monthly return is almost entirely driven by the performance of the 3/24 strategy, if this rank/hold period is excluded the next highest average monthly return is significantly lower at 1 per cent for the 3/12 strategy. Therefore, unless investors had the tenacity and foresight to hold onto their positions for the 24 month period, a significantly smaller return would have been achieved.

The reduced levels of momentum returns recorded during the global financial crisis period may be a result of the rapid rate of information diffusion. Referring to figure 2.1 and more specifically figure 2.2, Hong and Stein's (1999) model predicts that slow information diffusion leads to more pronounced momentum, through initial underreaction and subsequent overreaction. Presumably, during the global financial crisis period due to advances in information technology, information, and rumour, was rapidly reaching investors therefore, perhaps a possible reason for the reduced presence of momentum during this time period.

The overall poor performance of the momentum strategy from 2005 to 2012, contradicts the findings of Siganos and Chelley-Steeley (2006) for the London Stock Exchange, who report that momentum profits are more pronounced following a downturn in the market. The poor performance of the strategy during this time frame may also be due to the increased levels of volatility experienced during those credit crisis years. Wang and Xu (2015) document a similar pattern of momentum performance during the early part of 2009 and historically for instances in the 1930s and 1970s, when perhaps similar levels of volatility were present in markets. Geczy and Samanov (2013) observe similar patterns of momentum performance in the US market following the crash of 2008.

The adoption of a contrarian strategy during this time period would have generated returns over 1 per cent on two occasions (6/3, 6/9). Indeed, a contrarian strategy that only bought loser portfolios would generate returns of over 1 per cent on eleven occasions. Notably, for six-month rank periods, the loser portfolios perform particularly well.

Moreover, during the financial crisis period, winner portfolios contribute nearly 60 per cent of the overall return; in contrast O'Keeffe and Gallagher (2014) report loser portfolios contribute over 80 per cent of the return for the Irish market after the credit crisis collapse in 2007. However, as was the case with many international markets, a ban on short-selling between October 2008 and January 2009 for financial stocks came into effect in the UK market and would have hindered performance of the momentum strategy. Furthermore, when short-selling is possible the percentage of investors engaging in the practice may be miniscule, as De Bondt and Thaler (1985) propose as little as 0.29 per cent of individual investors engage in short-selling.

Return continuation is only present for winner portfolios during the global financial crisis period as loser portfolios register positive returns in 21 of the 25 rank and hold combinations. Jegadeesh and Titman (1993) observe return continuation in only the winner portfolios for all rank/hold combinations.

A distinct pattern of reversal in returns is present in the Internet bubble period, with evidence of reversal for all rank periods after an 18 month time frame; this is marginally longer than the one-year time period suggested by De Bondt and Thaler (1985). The presence of reversal in the Internet bubble years implies some level of overreaction within the market. The lack of evidence of reversal in the overall time period implies that overreaction may not be the cause of momentum. The combination of a short rank and long hold period, imply that momentum in the UK market is a medium-to-long term phenomena, this is conflicting to short-to-medium term timeline postulated by Jegadeesh and Titman (1993) for US data.

Perhaps the higher levels of momentum observed during the earlier years of the sample may be due to the slower diffusion of information throughout the market compared to the increasing rate information is disseminated throughout the market in the later sub-sample period, the slow levels of information diffusion leads to more underreacction within the market a possible exacerbating factor in pronouncing momentum. Hong and Stein's (1999) model (figure 2.2) highlights the impact of information diffusion on momentum levels within stock markets. Furthermore, as Hong *et al.* (2000) observe that low levels of analyst coverage pronounces momentum, it is assumed that due to the nature of financial markets in the early part of the 21st century the level of analyst coverage would have high, thus this may be a contributing factor to the reduced levels of momentum observed during this time period

6.2.2 Industry momentum

Industry momentum strategies offer an alternative trading strategy to investors; Shynkevich (2013) state that industry groupings are one of the most popular grouping factors used by investors. For the UK market between 1995 and 2015, individual momentum strategy performance is far superior to industry momentum, with the returns of industry momentum three and four percentage points less than individual momentum returns. In contrast, the seminal study on industry momentum performance in the US by Moskowitz and Grinblatt (1999) state that industry momentum should be the better performing strategy. However, this study's findings confirm the work of Conrad and Kaul (1998) who assert that industry returns should be less than individual returns, as the cross-sectional variation in mean industry returns is less than for individual stock returns.

Notably, for the industry strategies winner and loser portfolios act as expected, i.e. winners continue to win and losers continue to lose, on all but one occasion (18/24). In contrast winner portfolios produce negative returns in nine instances for individual momentum strategies. As is the case with individual momentum strategies the short-rank and long holding period strategy continues to remain the optimum industry momentum strategy. The three and six-month rank strategy perform particularly well, achieving over 1 per cent returns when the hold period exceeds nine months. Likewise, Fraulo and Nguyen (2009), Scowcroft and Sefton (2005) and Giannikos and Ji (2007) for US and international markets, observe six-month rank periods performing well for industry momentum strategies.

The performance of industry momentum during the global financial crisis period is more volatile for the various rank and hold combinations, with no combination generating more than a 1 per cent return per month. The 1 per cent return would potentially struggle to cover any associated transaction costs of the strategy. In comparison to the individual momentum returns during the same time period, with the elimination of the 3/24 strategy, the returns are not dissimilar.

Interestingly, it is during this time frame that the optimum strategy consists of a rank period greater than three months, in fact the 18/18 combination is the optimum strategy, implying momentum the global financial crisis period is a long-term effect. The long-term aspect of industry momentum between 2005 and 2012 differs from the findings of Moskowitz and Grinblatt (1999) who report that industry momentum dissipates in the US after twelve months. However, for the overall time frame there may be some partial reversal after twelve months.

Examining the impact if financial stocks are excluded from the analysis during the financial crisis period, a significant difference in the level of returns is apparent. By replacing the financial industry with the next best (worst) performing industry in the winner (loser) portfolios, the average monthly industry momentum return increases to 1.5 per cent with a 6/24 strategy. Furthermore, with the elimination of financial stocks from the strategy, short-sale restrictions are not applicable to investors during the temporary ban of late 2008 early 2009.

Hong and Stein (1999) postulate that the rate of information diffusion is directly correlated with performance of the momentum strategy and an industry with a low rate of diffusion could potentially have more pronounced momentum as information would disseminate throughout the market slowly, leading to underreaction. Therefore, during the global financial crisis period, in the BFI sector in particular, there would have presumably been an intense level of analyst activity, thus information would have dispersed throughout the market at a rapid pace. Hence, momentum may be not as pronounced during this time frame for that reason. Additionally, Daniel *et al.* (1998) assert that in calm markets momentum is strong, thus another potential reason for the lack of momentum returns during this volatile market period.

During the Internet bubble period industry momentum significantly underperforms individual momentum strategies. Similar to Moskowitz and Grinblatt (1999) average monthly industry returns in the US dissipate after a period of twelve months in general, with reversal evident for most rank and hold periods. Scowcroft and Sefton (2005) find that industry momentum between 1992 and 2003 in the MSCI index is largely driven by the presence of the tech-bubble and the performance of that sector. However, with the omission of TTM sector stocks the results of industry momentum between 1995 and 2002, do not change materially. Therefore, any rise in tech stocks prior to the crash did not augment overall industry momentum in that period.

The reason for the difference in performance of industry momentum in the two crisis periods may be due to the number of stocks in each of the associated sectors most affected by the technology and financial crash. Technology, telecommunications and media stocks accounted for a significantly small percentage of overall stocks in the Internet bubble period, compared to BFI sector stocks in the financial crisis period (12 equities versus 33). The performance of the BFI sector during the financial crisis period would therefore, have a far more lasting and sizeable impact on the overall stock markets; hence the observed increase in average monthly returns when the BFI sector is omitted from the sample.

Additionally, the deterioration in the performance of industry momentum in the global financial crisis period may be a result of the increase in the rate of information diffusion in the market as a whole during the years in question. Figure 2.2 depicts the model of Hong and Stein (1999) and the impact increased rates of information diffusion in the market can have on momentum returns.

6.3 Optimism in analysts' recommendations

The level of analyst optimism is addressed by examining the frequency of positive and negative recommendations issued by analysts. Prior studies have noted the perceived tendency for analysts to issue optimistic recommendations for a variety of reasons. Cowles (1944) is one of the first to suggest that analysts' forecasts and output tend to be over-optimistic. The time frame of analysis for this study includes periods of unique economic circumstance and the behaviour of analysts in the market is of key concern. Identifying if analysts are overly optimistic in the years and months prior to a significant economic downturn or event may imply either one of two things; 1) analysts are trying to instil waning confidence in the market and prevent the impending economic catastrophes by being optimistic in the their predictions; or 2) analysts are not fully informed about current market conditions and thus issue inaccurate and untimely recommendations for a variety of reasons.

Barber *et al*. (2006) observe that *buy* and *strong buy* recommendations account for 74 per cent of total recommendations in the US market by mid 2000, the results of this study are not dissimilar to their findings; with *buy* and *strong buy* recommendations accounting for 61 per cent of total recommendations in 2000 and *sell* and *strong sell* recommendations accounting for just 7 per cent. During the peak years of the tech-bubble an upward trend in the percentage of optimistic recommendations is apparent, however in the years after the crash the percentage of negative recommendations increase by 4 percentage points. In the US, Jegadeesh and Kim (2006) observe similar levels of negative recommendations in the early millennium years.

The average ratio of *buy-to-sell* recommendations of 5:1 between 1995 and 2002 is marginally higher than the ratio of 3.9:1 reported for the UK market by Jegadeesh *et al.* (2004). Conversely, Michaely and Womack (2004) report a markedly higher ratio of 10:1 in the mid-1990s for a US based study. The steep increase in the ratio of *buy-to-sell* recommendations in the years immediately preceding the Internet bubble collapse perhaps suggests analysts were not fully aware of some fundamental information concerning tech companies. Ang and Ma (2001) mute similar sentiments regarding analysts in the years immediately after the Asian financial crisis. However, in the immediate years following the tech-bubble burst the ratio of *buy-to-sell* recommendations decreases dramatically and is supported by the reduction in the number of *strong buy* recommendations during this period. The considerable reduction in optimistic recommendations implies analysts were at least quick to react to ongoing events and adjust their recommendations to reflect the current market outlook.

Stocks in the TTM sector are particularly affected by events relating to the Internet bubble, a peak level of 64 per cent positive recommendations is similar to the observations of Barber *et al.* (2006). The reduction in the level of optimistic recommendations in the TTM sector post 2000, insinuates analysts did readjust their recommendations accordingly. This is further supported by the reduction in the ratio of *buy-to-sell* recommendations from peak levels of 15:1 in 1997 onwards; implying analysts may have noticed that the market was somewhat over-inflated in the years prior to the tech-bubble bursting. The level of neutral recommendations increases in 2001 and 2002, which may imply that analysts were not optimistic about the TTM sector but were perhaps apprehensive to issue a *sell* or *strong sell* recommendations for fear of incurring the wrath of investment managers or lucrative clients. Furthermore it must be noted that 1997 was the year of Tony Blair's landslide victory over John Major and 2001 included the events of 9/11 and the tail end of the dot.com collapse.

The global financial crisis, a number of years later, was arguably more damaging than the Internet bubble collapse, as the number of investors involved in the stock market was significantly larger, and the consequences of the financial crisis were far less discriminating in nature. Furthermore, trading restrictions such as short-sell bans were put in place for lengthy periods of time in several international financial markets. A short-selling ban took effect in the UK market on the 19th of September 2008 until January 16th 2009 and although confined to financial stocks, it limited the trading abilities of investors.

In 2007 and 2008, years that included the crisis at Northern Rock, triggering the first UK bank run in over a century, and the collapse of Lehman Brothers, optimistic recommendations still accounted for over 50 per cent of total recommendations. Analysts were either totally oblivious to the ongoing market turmoil or attempting to negate the impact of such events by instilling a perceived confidence in the market. The 5.3:1 ratio of *buy-to-sell* recommendations is higher than the 2.3:1 that is observed by Ryan and Taffler (2006) for the UK market, albeit for an earlier time period (1993-

1995), but significantly less than the ratio of 7.1:1 reported by Ho and Harris (1998) for the US market.

In regards to the percentage of recommendations deemed optimistic in the global financial crisis period, the behaviour of analysts is quite different to that observed during the Internet bubble period. Rather than a re-adjustment in the months after the crash, the ratio of *buy-to-sell* recommendations continues to increase upward, reaching a peak in 2012. This is similar to the trend observed in Asian data by Ang and Ma (2001) with regard to analysts failing to fully adjust during the post-crash period.

The BFI sector is the focal point of the global financial crisis period and is the only sector within the UK that is subject to the short-selling restrictions of late 2008 and early 2009. In the years preceding the financial crisis, *hold* recommendations account for the largest proportion of total recommendations, signifying that analysts may have been aware of the impending turmoil but were reluctant to issue negative recommendations. However, in 2008 and 2009 an increase in the frequency of *sell* and *strong sell* recommendations is evident, indicating analysts did react to the financial situation and adjust their recommendations in the BFI sector.

The reason for the level of optimism recorded during the two time periods may perhaps be a result of an increase in the conflicts of interest analysts face particularly during times of economic crisis, when it may be likely that pressure is applied on analysts to not exacerbate the crisis further. Moreover, the perceived optimism may be a result of analysts' following and recommending stocks that have previously done well (momentum) or so-called glamour stocks, in order to issue more positive recommendations and forecasts.

6.4 Can analysts' advice be relied upon?

The value of analyst output has been continually debated in research literature since the illustrious study of Cowles (1933). Investors rely heavily on the advice of analysts' recommendations during the Internet bubble and global financial crisis periods, this section discusses if the recommendations are of investment value to investors by observing the behaviour of stock returns around a 13-month investment window.

In the years prior to the Internet bubble implosion, a clear separation between the two most extreme recommendation categories (*strong sell and strong buy*) is apparent. The movement in stock returns prior to the recommendation issue suggests analysts are price followers rather than price formers, i.e. analysts are momentum traders rather than new market makers. Aitken *et al.* (2000) observe similar trends in Australian data and state that analysts are more reactive than proactive and the upward trend in returns prior to the recommendation issue date implies analysts are either followers of momentum or their recommendation is a delayed reaction to good news. Moreover, the observed increase in returns prior to the recommendation issue date insinuate analysts' issue recommendations for stocks that previously performed well, i.e. they are market followers rather than market makers; Bange and Miller (2004) document similar trends in a US based study. O'Brien and Tian (2006) report evidence of past stock returns influencing analysts' recommendations in the period 1996 to 2000.

In agreement with the findings of Stickel (1995) that the extreme recommendation generates the greatest return, the *strong buy* recommendation generates the largest return for stocks in the TTM sector prior to April 2000. On adjustment of returns by the FF3F model, the clear separation between the extreme recommendations remains, implying the FF3F model does not capture potential risk of the CRRs.

The largest price reaction for negative recommendations occurs in the six months after the recommendation issue date, suggesting that investors are reluctant to acknowledge bad news and hold onto losers in a bid to avoid the regret associated with realising loses (the disposition effect); Ryan (2006) reports similar findings for the Irish market. After the Internet bubble burst, the largest decline in returns is observed in the one-month prior to recommendation issue; however unlike Ryan (2006) who reports that observation for negative recommendations only, the findings of this study observe the occurrence for all recommendation categories.

After the tech-bubble burst, both the CARs and CRRs are higher, but negative, in the months prior to the recommendation issue date for all categories. Returns for all categories continue to decline in the six months after recommendation issue, implying poor overall performance in all categories. However, *strong buy* recommendations still outperform *strong sell* recommendations and the adoption of a long/short strategy in the years after the Internet bubble generates significant returns up to six months after the issue month; therefore analysts' recommendations do contain investment value after the Internet bubble bursts.

Analysts' recommendations during the global financial crisis period have an impact on returns perhaps not in the way expected. When returns are adjusted for risk prior to the financial collapse, *strong sell* recommendations outperform *strong buy* recommendations in the months prior to recommendation issue date. This is reflected in the larger contribution of the loser portfolio to momentum returns during this time period. As a consequence of *strong sell* recommendations outperforming *strong buys,* a long/short strategy will only be viable if analysts' recommendations are inverted, to buy *strong sell* and by selling stocks bearing a *strong buy* recommendation.

All recommendation categories perform poorly after September 2007, with *strong sell* recommendations continuing to substantially outperform *strong buy* recommendations for the 13-month event window. This is a clear indication of the deterioration in the accuracy of analysts' recommendations after the financial meltdown of September 2007. A similar deterioration in the accuracy of analysts' is documented by Arand and

Kerl (2012) between 2007 and 2009. Sidhu and Tan (2011) report similar evidence of poor analyst performance during the financial crisis in the Australian market.

Analysts' advice only contains investment value during the global financial crisis years if the investors invert analysts' recommendations, i.e. long *strong sells* and short *strong buys.* However, the short-selling ban on BFI stocks between September 2008 and January 2009 would have limited the potential of reaping such returns. It may be possible that the impact of the poor analyst performance was limited as perhaps the smart money would have already exited the market. The lack of evidence supporting a stable relationship between analysts' advice and average monthly stock returns at the aggregate level implies that analysts did not exacerbate the financial crisis. Kothari *et al.* (2006, pg. 566) report similar evidence that 'the market's reaction to aggregate earnings differs dramatically from its reaction to firm earnings'.

The lack of analyst influence on stock returns at least at the aggregate level may perhaps be due to prices better anticipating earnings growth at the aggregate level, as documented by Sadka and Sadka (2009). Furthermore, predicting the earnings outcome of individual firms may be a more difficult task than at the aggregate level hence the reduced impact of analysts' advice at the aggregate level.

The connection between the reduced returns of industry momentum compared to individual momentum and the lack of impact of analysts' advice at the aggregate level compared to firm-level, must also be considered. Perhaps analysts' drive momentum far more than previously thought and thus their influence at the firm-level may pronounce momentum.

6.5 Chapter summary

In this chapter the main findings of this study are discussed in detail. The performance of individual momentum throughout the time period and its particular magnitude during the Internet bubble period is addressed. The pronouncement of momentum in the earlier years of this study, concur with the findings of Hon and Tonks (2003) and Galariotis *et al.* (2007) that momentum is more pronounced in the latter half of the 1990s and dissipates in the millennium years.

The optimum strategies in all time periods for individual momentum consist of a three-month rank period and either a 18 or 24 month hold period; substantially shorter rank periods compared to those suggested by Jegadeesh and Titman (1993) and Rouwenhorst (1999). The presence of a reversal is not evident in the overall time frame for the three-month rank periods but is present for the other ranking periods. Evidence of reversal is apparent after a period of 18 months during the Internet bubble period, indicating momentum may at least in part be due to some level of underreaction.

Industry momentum does not generate substantial returns compared to individual momentum, contrary to the findings of Moskowitz and Grinblatt (1999) for the US, but is present in all time periods of analysis. The elimination of TTM stocks during the Internet bubble period had no material impact on the level of industry returns, however, the omission of BFI sector stocks during the global financial crisis years, drastically increased the level of industry return recorded.

The presence of partial reversal in many momentum scenarios indicate that momentum may in part be due to underreaction. Whilst, no definitive conclusion can be drawn as to the cause of the phenomenon, perhaps it is a combination of factors, presented in figure 2.1, which may impact on the performance of momentum. However, one cannot ignore that market states may also impact on momentum returns, as evidenced by the differing momentum returns during certain market conditions.

Analysts appear to be optimistic in the years prior to the tech-bubble burst but not excessively so in comparison to other international studies. Analysts' advice is also of investment value to investors both before and after April 2000 in the immediate months surrounding the recommendation issue date.

Analysts appear to show increased levels of optimism in the years after the global financial crisis, possibly in an attempt to stabilise the market and instil some confidence. Deterioration in the accuracy of analysts' recommendation is noted, confirming the findings of Arand and Kerl (2012). Furthermore, a long/short strategy is profitable when analysts' recommendations are inverted, to imply the purchase of stocks bearing *strong sell* recommendations, funded by the selling of stocks bearing a *strong buy* recommendation.

Chapter Seven – Conclusion

7.1 Introduction

This concluding chapter summarizes the entire study; in section 7.2 the key research questions set out in the introductory chapter are restated, section 7.3 revisits the key findings of the study, section 7.4 includes a brief discussion pertaining to the implications of the key findings. The contribution of this study is outlined in section 7.5 and potential limitations of the study are addressed in section 7.6. Finally, section 7.7 outlines avenues for possible future research.

7.2 Research objectives

This section reiterates the key research objectives of this study as outlined in the introductory chapter. The overarching aim of this study was to determine profitability of the momentum trading strategies in the UK stock market between 1995 and 2015. Furthermore, this study focused on the role of analysts' recommendations in the market and the potential value of their recommendations.

The research questions as previously outlined in chapter one are;

1) Is momentum present in the UK stock market between 1995 and 2015 and if so is it possible to make abnormal returns by following the strength-rule strategy?
2) Is momentum more pronounced in industries?
3) Is momentum more pronounced during certain time periods?
4) Were analysts' recommendations accurate during times of economic crises?

5) Did analyst behaviour exacerbate the financial crises?

Asset pricing models were used to determine the performance of strength-rule strategies from both an individual stock and industry perspective; several different combinations or rank and hold periods were examined. As well as examining the overall performance of momentum between 1995 and 2015, certain time periods were isolated to examine its performance in times of economic crisis. Furthermore, the value of analysts' recommendations was tested by observing potential stock returns if a long/short strategy was adopted based on analysts' recommendations, with particular focus on the TTM and BFI sectors during the Internet bubble and global financial crisis periods.

7.3 Key findings

The key findings pertaining to momentum are summarised in section 7.3.1 and the key results of the observation of analysts' recommendations are presented in section 7.3.2. Analysis of the evidence signifies momentum is present in the UK stock market between 1995 and 2015, and the value and accuracy of analysts' recommendations appears to deteriorate in later years of this study.

7.3.1 Momentum findings

Chapter five documented the key findings in relation to momentum in the UK stock market. Overall, implementation of the strength-rule strategy between 1995 and 2015 generates significant returns for portfolios consisting of individual equities. The presence of momentum in the UK stock market is consistent with the findings of Hon and Tonks (2003) and Chelley-Steely and Siganos (2004).

Under market efficiency the performance of returns should not be dependent on the performance of past returns; however, this study documents evidence of positive autocorrelation in stock returns and thus rejects the null hypothesis of market efficiency as returns can be generated by trading on the basis of past performance of returns.

In general the optimal momentum strategy consisted of a short rank period and long hold period; contrary to prior studies such as Jegadeesh and Titman (1993) and Rouwenhorst (1998) who find that a short hold period and long rank period combine to generate the highest momentum return in US markets. Hon and Tonks (2003) also report a 12/3 trading strategy as generating the highest momentum return in the UK market. Additionally, in agreement with the aforementioned studies, it is observed that for the optimum strength-rule strategy, winners and losers contribute evenly to overall momentum return.

The performance of strength-rule strategies is particularly apparent in the Internet bubble years (1995-2002) with substantially higher returns compared to the other time periods of analysis. During the global financial crisis years the strength-rule strategy does not perform as consistently, with the optimum strategy (3/24) very much an outlier.

In all time periods the individual momentum strategy outperformed the industry momentum strategy by a considerable margin, in contradiction to the findings of Moskowitz and Grinblatt (1999). Industry momentum returns are still possible in all periods; however, in some instances the momentum return may not be adequate to cover any potential transaction costs. The exclusion of TTM sector stocks during the Internet bubble does not alter industry returns substantially; however, industry momentum returns increase considerably with the omission of BFI sector stocks during the global financial crisis period.

7.3.2 Analysts' recommendations

Chapter five also documented the perceived optimism in analysts' recommendations and the impact of their recommendations on stock returns. Prior to the Internet bubble implosion analysts' recommendations contain an element of optimism, with the *buy-to-sell* ratio slightly higher than previously documented by Jegadeesh *et al.* (2004) for the UK market. Furthermore, *buy* and *strong buy* recommendations account for 64 per cent of total recommendations in the TTM sector during the year of the tech-bubble bursting. This figure reduces to 45 per cent in the year immediately after, suggesting analysts re-adjust their recommendations in line with market conditions.

In the years preceding the global financial crash the level of *buy* and *strong buy* recommendations steadily increased, implying analysts were either not aware of the impending financial collapse or were reluctant to issue negative recommendations for a variety of possible reasons. Notably, in the years preceding the collapse neutral recommendations account for the largest percentage of recommendations in the BFI sector, indicating that perhaps analysts preferred to issue neutral recommendations than a negative rating to avoid the wrath of investment-banking managers.

Evidence from before and after the Internet bubble burst suggests that analysts' recommendations do contain investment value as returns can be made when a long/short strategy is implemented. Moreover, the increase in stock returns in the months prior to the recommendation issue date implies analysts are market followers (momentum followers) rather than market movers; similar evidence is reported by Aitken *et al.* (2000) and Groth *et al.* (1979). During the global financial crisis period, analysts' recommendations were not as accurate, when the inversion of analysts' recommendations is a more profitable option for investors, i.e. funding the purchase of *strong sell* recommendations by shorting *strong buy* recommendations. However, it must be noted that profits would have been curtailed in the BFI sector as short-selling restrictions applied to financial stocks for a short period of time.

On an aggregate level no stable relationship was found between the various measurements of analyst advice and the average monthly stock market returns, suggesting that analysts did not exacerbate the financial crisis as their advice had a limited impact on average monthly returns.

7.4 Implications

The findings of this study have implications for investors, academics and regulators. From an investors point of view momentum trading strategies are profitable in the UK stock market between 1995 and 2015. The level of momentum return does appear to show a declining trend of profitability from the highs experienced during the Internet bubble crisis to the declining and inconsistent trend during the global financial crisis period.

Industry momentum strategies are not as profitable in the UK market; therefore forming an investment portfolio on the basis of individual stock performance is the wiser investment decision. Furthermore, skipping a month between rank and hold periods does not alter returns materially. Momentum is a long-term effect in the UK market with reversal not evident for three-month rank periods up-to a period of 24 months.

The even contribution of winner and loser portfolios to the optimum strategies implies that profits can still be generated in a number of instances if trading winner portfolios only; an imperative implication given the short-selling restrictions that may be imposed and individual investors' inability to short-sell, as highlighted by De Bondt and Thaler (2008). The omission of industries acutely affected by an ongoing crisis from momentum strategies can increase industry momentum returns as seen by the evidence from the global financial crisis period.

The level of optimism viewed in analysts' recommendations and the perceived reluctance to issue negative recommendations in times of economic crisis implies an element of conflict in the recommendations analysts issue in the UK. This surely will encourage ongoing monitoring by regulators in the UK.

Evidence from this study suggests that analysts are momentum traders, evidenced by the increase in stock returns prior to recommendation issue date. Analysts' recommendations contain an element of investment value during the Internet bubble period; however, during the global financial crisis period analysts' recommendations were not as accurate or as valuable a guide to profitable trading. Analysts' reliability appears to worsen when investors need it most, as the deterioration in the accuracy of their recommendations during the global financial crisis signifies.

7.5 Contribution

This study contributes to existing prior literature in a number of ways. Firstly, the inclusion of periods of economic turmoil allows the relationship between momentum performance and market states to be addressed. Momentum is a well documented and persistent anomaly in several international markets, determining its consistency during times of economic chaos when investors require a steady investment option is critical. Moreover, sub-period analysis tests the findings of Hon and Tonks (2003) that momentum may only be present in the UK market for certain periods of time.

Comparison of the performance of individual and industry momentum is also critical, as industry groupings are one of the most commonly used grouping factors by investors (Shynkevich, 2013). Analysis of industry momentum in the UK market is neglected in prior literature, this study address that research gap. Furthermore, industry momentum is assessed with the omission of industries that are most acutely affected by certain economic crisis, thereby determining their relevance to the overall performance of industry momentum.

During times of economic turmoil the market is often inundated with misleading and excessive amounts of information and rumours, it is during these periods that investors often require the guidance of analysts most. Therefore, examining their accuracy during times of crisis and assessing the value encapsulated within their output is essential. Evaluating the level of optimism in analysts' recommendations before and after an event is vital to appraising the potential level of conflict possessed by analysts. Evaluation of the UK stock market with respect to momentum and the behaviour of analysts during the internet bubble period and global financial crisis period is limited in prior studies, this study adds to what little existing research there is.

7.6 Limitations

The conclusions of this study are constrained by a certain number of limitations relevant to various aspects of this study and thus conclusions should be interpreted accordingly. Within this study transaction costs are not explicitly accounted for, however returns are deemed significant if they are sufficiently above a given threshold outlined by prior literature to cover applicable transaction costs. Vayanos (1998) state that transaction costs primarily affect the length of holding period and trading volumes.

A minimal amount of firm data is excluded from the study due to incomplete or unavailable historical data; however, no systematic survivorship bias is present. Every effort is made to include all companies that are listed at any given time on the FTSE100 index between 1995 and 2015.

The sub-sample time periods selected in this study include periods of economic turmoil and although it captures the relationship between momentum and market conditions, it would be of benefit to extend this study to include out-of-sample analysis to determine the profitability of the momentum strategies in a period of relative economic stability. Similarly, the analysis of the value of analysts' recommendations is confined to TTM and BFI sector stocks; it may be of benefit to determine if analysts' recommendations encapsulated investment value in sectors not principally affected by the Internet bubble or global financial crisis.

Additionally, this study is purely a quantitative study and although this allows for the in-depth analysis of a broad ranging dataset from a number of perspectives, the inclusion of a qualitative element may add to the study; particularly with regard to the behaviour of analysts' where a qualitative approach may reveal the process of how analysts reach recommendation decisions.

7.7 Recommendations for future research

This study incites several channels for further research. Evaluating the prominence of momentum in an out-of-sample time frame will enable a more robust conclusion to momentum existing in a time of relative economic stability. The performance of momentum strategies with a very short rank period and long hold period merits further research as it is in contrast to prior literature pertaining to the optimal momentum strategy. Even though no significant difference was found between the regular strength-rule strategy and the skip-strategy; motivated by the work of Novy-Marx (2012), further research is warranted to determine what is the optimal length of time left between the end of the ranking period and the beginning of portfolio formation.

Furthermore, the presence of industry momentum in the UK is highlighted, additional research may isolate if momentum is more pronounced in certain industries or if industries with certain characteristics are more prone to momentum. Similarly, this study focuses primarily on stocks in the FTSE100; analysis of momentum in the constituents of the FTSE350 and smaller stocks would be of a good comparison.

Further analysis of momentum during the global financial crisis years is warranted as with the exception of the optimum strategy (3/24) the next best performance strategy produces a substantially lower return. It would be interesting to determine if the elimination of certain stocks from this period alters the outcome of momentum strategies.

Moreover, as suggested by Chui *et al.* (2010) decision-making and investment behaviour differ greatly between cultures, perhaps future research is warranted to study the performance of the momentum strategy in emerging markets, or in markets that contain different cultural characteristics to the UK market.

The performance of analysts in sectors other than the TTM and BFI sectors during the sub-sample periods warrants further investigation to determine if analysts observed deterioration in performance is isolated to those sectors or a market wide occurrence. Furthermore, the performance of analysts in times of relative market stability would facilitate a benchmark to measure analyst performance during un-stable economic times such as the Internet bubble and global financial crisis.

The observed optimism in analysts' recommendations is an ongoing issue and future research is required to determine the effectiveness of any regulatory efforts to reduce the conflicts of interest that analysts may endure. Additionally, research on the value of analysts' recommendations in other markets would provide a suitable comparison as to whether analyst behaviour can be generalised to markets other than the UK. It is also yet to be determined what, if any, the effect of the recent Brexit vote will have on the regulatory environment in the UK; close and consistent monitoring will be required to evaluate any potential impact.

References

Agapova, A. and Madura, J. (2013) ‘Impact of Galleon case on insider trading prior to company issued guidance’, *Journal of Applied Finance,* 23(2), 185-198.

Agrawal, A. and Chen, M.A. (2004) ‘Analyst conflicts and research quality’, *Quarterly Journal of Finance,* 2(2), 1-40.

Agyei-Ampomah, S. (2007) ‘The post-cost profitability of momentum trading strategies: Further Evidence from the UK’, *European Financial Management,* 13(4), pp.776-802.

Aitken, M. and Frino, A. (1996) ‘Execution costs associated with institutional trades on the Australian stock exchange’, *Pacific-Basin Finance Journal,* 4(1), 45-58.

Aitken, M., Muthuswamy, J. and Wong, K.L. (2000) ‘The impact of brokers’ recommendations: Australian evidence’, *University of New South Wales, conference paper,* [online] available at www.sirca.org.au.

Albuquerque, R. and Miao, J. (2010) ‘Advance information and asset prices’, *working paper,* [online] available at https://ideas.repec.org/p/red/sed008/44.html.

Ali, A. and Trombley, M. (2006) ‘Short-selling costs and momentum in stock returns’, *Journal of Business Finance and Accounting,* 33(3-4), pp. 587-615.

Altinkilic, O. And Hansen, R. (2009) ‘On the information role of stock recommendation revisions’, *Journal of Accounting and Economics,* 48(10), pp. 17-36.

Alwathainani, A, (2013) ‘It’s all overreaction: Earnings momentum to value/growth’, *Journal of Behavioural Finance and Economics,* 3(1), pp. 72-98.

Alwathaninani, A. (2012) ‘Consistent winners and losers’, *International Review of Economics and Finance,* 21(1), pp. 210-220.

Ang, J. and Ma, Y. (2001) 'The behaviour of financial analysts during the Asian financial crisis in Indonesia, Korea, Malaysia and Thailand', *Pacific-Basin Finance Journal,* 9 (3), pp. 233-263.

Antoniou, A., Galariotis E., and Spyrou S. (2006a) 'The effect of time-varying risk on the profitability of contrarian investment strategies in a thinly traded market: a Kalman filter approach', *Applied Financial Economics,* 16(18), pp.1317-1329.

Antoniou, A., Galariotis E., and Spyrou S. (2006b) 'Short-term contrarian strategies in the London Stock Exchange: Are they profitable? Which factors affect them?', *Journal of Business Finance and Accounting,* 33(5-6), pp.839-867.

Arand, D. and Kerl, A. (2012) 'Analyst research and investor reactions: Evidence from the 2008 financial crisis', [online] available at http://ssrn.com/abstract=2126605

Arena, M., Haggard, S. and Yan, X. (2008) 'Price momentum and idiosyncratic volatility', *The Financial Review,* 43(2), pp.159-190.

Arnold, L. and Brunner, S. (2015) 'The economics of rational speculation in the presence of positive feedback trading', *Quarterly Review of Economics and Finance,* 57, pp. 161-174.

Ashley, J. (1962) 'Stock prices and changes in earnings and dividends: Some empirical results', *Journal of Political Economy,* 70(1), pp. 82-85.

Asness, C., Liew, J. and Stevens, R. (1997) 'Parallels between the cross-sectional predictability of stock and country returns', *Journal of Portfolio Management,* 23(3), pp. 79-87.

Asness, C., Moskowitz, T. and Pedersen, L. (2013) 'Value and momentum everywhere', *Journal of Finance,* 68(3). pp. 929-985.

Bacmann, J. F., Dubois, M. and Isakov, D (2001) 'Industries, business cycles and profitability of momentum strategies: An International Perspective', [online] available at http://ssrn.com/abstract=264657.

Badrinath, S. and Wahal, S. (2002) 'Momentum Trading by Institutions', *Journal of Finance,* 57(6), pp. 2449-2478.

Bailey, W., Li, H., Mao, C. and Zhong, R. (2003) 'Regulation fair disclosure and earnings information: Market, analyst and corporate response', *Journal of Finance,* 58(6), pp. 2487-2514.

Ball, R, and Brown, P. (1968) 'An empirical evaluation of accounting income numbers', *Journal of Accounting Research,* 6 (2), pp. 159-178.

Balvers, R. and Wu, Y. (2006) 'Momentum and mean reversion across national equity markets', *Journal of Empirical Finance,* 13(1), pp. 24-48.

Bange, M. (2000) 'Do the portfolios of small investors reflect positive feedback trading?', *The Journal of Financial and Quantitative Analysis,* 35(2), pp. 239-255.

Bange, M. and Miller, T.W. (2004) 'Return momentum and global portfolio allocations', *Journal of Empirical Finance,* 11(4), pp. 429-459.

Banz, R. (1981) 'The relationship between return and market value of common stocks', *Journal of Financial Economics,* 9(1), pp. 3-18.

Barber, B and Odean, T (2000) 'Trading is hazardous for your wealth: The common stock investment performance of individual investors', *Journal of Finance,* 55(2), pp. 773-806.

Barber, B. and Odean, T. (1999) 'The courage of misguided convictions', *Financial Analysts Journal,* 55(6), pp. 41-55.

Barber, B. and Odean, T. (2008) ‘All that Glitters: The effect of attention and news on the buying behavior of Individual and institutional investors’, *Review of Financial Studies*, 21(2), 785-818.

Barber, B., Lehavy, R. and Trueman, B. (2007) ‘Comparing the stock recommendation performance of investment banks and independent research firms’, *Journal of Financial Economics*, 85(2), pp.490-517.

Barber, B., Odean, T. and Zhu, N. (2009) ‘Do Retail Trades move markets?’, *Review of Financial studies*, 22(1), pp. 151-186.

Barber, B.M., Lehavy, R., McNichols, M. and Trueman, B. (2006) ‘Buys, holds, and sells: The distribution of investment banks’ stock ratings and the implications for the profitability of analysts’ recommendations’, *Journal of Accounting and Economics,* 41(1), pp.87-117.

Barberis, N. (2013) ‘Psychology and the financial crisis of 2007-2008’, *Haliassos M.(Ed.), Financial Innovation: Too much or too little?*, MIT Press, Cambridge, MA.

Barberis, N. and Shleifer, A., (2003) ‘Style investing’, *Journal of Financial Economics*, 68(2), pp. 161–99.

Barberis, N., Shleifer, A. and Vishny, R. (1998) ‘A model of investor sentiment’, *Journal of Financial Economics,* 49(3), pp. 307-343.

Barniv, R., Hope, O., Myring, M.J. and Thomas, W.B. (2009) ‘Do analyst practice what they preach and should investors listen? Effects of recent regulations’, *The Accounting Review*, 84(4), pp. 1015-1039.

Barroso, P. and Santa-Clara, P. (2015) ‘Momentum has its moments’, *Journal of Financial Economics,* 116(1), pp. 111-120.

Bekaert, G., Erb, C.B., Harvey, C.R., Viskanta, T.E., (1997), 'What matters for emerging market investments?', *Emerging Markets Quarterly,* 1(2), pp.17 – 46.

Berk, J.B., Green, R. and Naik, V. (2000) 'Optimal investment, growth options and security returns', *Journal of Finance,* 54(1), pp. 1553-1608.

Bernard, V.L and Thomas, J. (1989) 'Post earnings-announcements Drift: Delayed price response or risk premium?', *Journal of Accounting Research,* 27(3), pp 1-36.

Bhojraj, S. and Swaminathan, B. (2006) 'Macromomentum: Returns predictability in international equity indices', *Journal of Business,* 79(1), pp. 429-451.

Bhootra, A. (2011) 'Are momentum profits driven by the cross-section dispersion in expected stock returns?', *Journal of Financial Markets,* 14(3), pp. 494-513.

Bidwell, C. (1977) 'How good is institutional brokerage research?', *Journal of Portfolio Management,* 3(2), pp. 26-31.

Bilio, M., Cales, L. and Guegan, D. (2011) 'Portfolio symmetry and momentum', *European Journal of Operational Research,* 214(3), pp. 759-767.

Bird, R. and Casavecchia, L. (2007) 'Value enhancement using momentum indicators: The European experience', *International Journal of Managerial Finance,* 3(3), pp. 229-262.

Bird, R. and Whitaker, J. (2003) 'The performance of value and momentum investment portfolios: Recent experience in the major European markets', *Journal of Asset Management,* 4(4), pp. 221-246.

Bjerring, H., Lakonishok, J. and Vermaelen, T. (1983) 'Stock price and financial analysts' recommendations', *Journal of Finance,* 38(1), pp. 187-204.

Black, F. (1986) 'Noise', *Journal of Finance,* 41(3), pp. 529-543.

Black, F. (1993) ‘Estimating expected return’, *Financial Analysts Journal,* 9(5), pp.36-38.

Bloomfield, R., O’Mara, M. and Saar, G. (2009) ‘How noise trading affects markets: An experimental analysis’, *Review of Financial Studies,* 22(6), pp. 2275-2302.

Bloomfield, R., Taylor, W. and Zhou, F. (2009) ‘Momentum, reversal, and informed traders in laboratory markets’, *Journal of Finance*, 64(6), pp. 2535-2558.

Bradley, D., Jordan, B. and Ritter, J. (2003) ‘The quiet period goes out with a bang’, *Journal of Finance,* 58(1), pp. 1-36.

Camerer, C. (1989) ‘Does the basketball market believe in the ‘Hot-Hand’?’, *American Economic Review,* 79(5), pp. 1257-1261.

Campbell, J., Lettau, M., Malkiel, B. and Xu, Y. (2001) ‘Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk’, *Journal of Finance,* 56(1), pp. 1-43.

Campos-Vazquez, R. and Cuilty, E. (2014) ‘The role of emotions on risk aversion: A prospect theory experiment’, *Journal of Behavioural and Experimental Economics,* 50, pp. 1-9.

Carhart, M. (1997) ‘On persistence in mutual fund performance’, *Journal of Finance,* 52(1), pp. 57-82.

Chan, K. and Kot, K. (2006) ‘Price reversal and momentum strategies’, *Journal of Investment Management,* 4(1), pp. 1-20.

Chan, K., Allaudeen, H. and Wilson, T. (2000) ‘Profitability of momentum strategies in the international equity markets’, *Journal of Financial and Quantitative Analysis,* 35 (3), pp. 153-172.

Chan, K., Hameed, A. and Tong, W. (2000) ‘Profitability of momentum strategies in the international equity markets’, *Journal of Financial and Quantitative Analysis,* 35(2), pp. 153-172.

Chan, L., Jegadeesh, N. And Lakonishok, J. (1996) ‘Momentum strategies’, *Journal of Finance,* 51(5), pp. 1681-1713.

Chan, L., Karceski, J. and Lakonishok, J. (2007) ‘Analysts’ conflict of interest and biases in earnings forecasts’, *Journal of Financial and Quantitative Analysis,* 42(4), pp. 893-913.

Chan, W. (2003) ‘Stock price reaction to news and no-news: Drift and reversal after headlines’, *Journal of Financial Economics,* 70(2), pp. 223-260.7

Chelley-Steeley, P and Siganos, A. (2004) ‘Momentum Profits and macroeconomic factors’, *Applied Financial Letters,* 11(7), pp. 433-436.

Chen, C. and Chen, P. (2009) ‘NASD Rule 2711 and changes in analysts’ independence in making stock recommendations’, *The Accounting Review,* 84(4), pp. 1041-1071.

Chen, L., Moise, C.E. and Zhao, X.S. (2009) ‘Myopic extrapolation, price momentum, and price reversal’, [online] available at http://ssrn.com/abstract=1343812.

Chen, M. A., and Marquez, R., (2009) ‘Regulating Security Analysts’, *Journal of Financial Intermediation,* 18(2), pp. 259-283.

Cheney, H. (1970) ‘The value of industry forecasting as an aid to portfolio management’, *Financial Review,* 1(5), pp. 331-339.

Cheng, J.W. and Wu, H. (2010) ‘The profitability of momentum trading strategies: Empirical evidence from Hong Kong’, *International Review of Economics & Finance,* 19(4), pp. 527-538.

Cheung, K. and Coutts, J. (1999) 'The January effect and monthly seasonality in the Hang Sang Index 1985-1997', *Applied Economic Letters,* 6(1), 121-123.

Chiao, C., Hung, W. and Lee, C. (2011) 'Institutional trading and opening price behaviour evidence from a fast emerging market', *Journal of Financial Research,* 34(1), pp. 131-154.

Chira, I. and Madura, J. (2013) 'Impact of the Galleon case on insider trading prior to mergers', *Journal of Financial Research,* 36(3), pp. 325-346.

Chopra, V. (1998) 'Why so much error in analysts' earnings forecasts?', *Financial Analysts Journal,* 54(6), pp. 35-42.

Chordia, T, and Shivakumar, L. (2002) 'Momentum, business cycle and time varying expected returns', *The Journal of Finance,* 57(2), pp. 985-1019.

Christophe, S., Ferri, M.G. and Hsieh, J. (2010) 'Informed trading before analyst downgrades: evidence from short sellers', *Journal of Financial Economics,* 95(2), pp. 85-106.

Chu, H. H. and Chiang, M.H. (2010) 'The interaction between individual and industry momentum', *Investment Management and Financial Innovations,* 7(2), pp. 72-80.

Chui, A., Titman, S. and Wei, K.C. (2010) 'Individualism and momentum around the world', *Journal of Finance,* 65(1), pp. 361-392.

Clare, A. and Thomas, S. (1995) 'The overreaction hypothesis and the UK stock market', *Journal of Business Finance and Accounting,* 22(7), pp. 961-973.

Clayman, M. and Schwartz, R. (1994) 'Falling in love again: Analysts' estimates and reality', *Financial Analysts Journal,* 50(5), pp. 66-68.

Cohen, R., Gomper, P. and Vuolteenaho, T. (2002) ‘Who underreacts to cashflow news? Evidence from trading between individuals and institutions’, *Journal of Financial Economics,* 66(2-3), pp. 406-462.

Colker, S.S. (1963) ‘An analysis of security recommendations by brokerage houses’, *Quarterly Review of Economics and Business,* 3, pp. 19-28.

Conrad, J. and Kaul, G. (1998) ‘An anatomy of trading strategies’, *Review of Financial Studies*, 11(3), pp. 489-519.

Conrad, J. and Yavuz, D. (2012) ‘Momentum and reversal: Does what goes up always come down?’, [online] available at http://ssrn.com/abstract=2011148.

Conrad, J., Cornell, B., Landsman, W. and Rountree, B. (2006) ‘How do analyst recommendations respond to major news?’, *Journal of Financial and Quantitative Analysis,* 41(1), pp. 25-49.

Cooper, M.J., Gutierrez, R. and Hameed, A. (2004), ‘Market states and momentum’, *Journal of Finance,* 59(3), pp. 1345-1365.

Corner, A., Harris, A. and Hahn, U. (2010) ‘Conservatism in belief revision and participant scepticism’, *Proceedings of the 32nd Annual Conference of the Cognitive Science Society 2010.*

Cornett, M., Tehranian, H. and Yalcin, A. (2007) Regulation fair disclosure and the market’s reaction to analyst investment recommendation changes, *Journal of Banking and Finance*, 31(3), pp. 567-588.

Corrado, C.J. and Truong, C. (2008) ‘Conducting event studies with Asia-Pacific security market data’, *Pacific-Basin Finance Journal,* 16(5), pp. 493-521.

Corredor, P., Ferrer, E. and Santamaria, R. (2014) 'Is cognitive bias really present in analysts' forecasts? The role of investor sentiment', *International Business Review,* 23(4), pp. 824-837.

Coval, J. and Shumway, T. (2005) 'Do behavioural biases affect prices', *Journal of Finance,* 60(1), pp. 1-34.

Cowen, A., Groysberg, B. and Healy, P. (2006) 'Which types of analyst firms are more optimistic?', *Journal of Accounting and Economics,* 41(1), pp. 146-199.

Cowles, A (1944) 'Stock market forecasting', *Journal of Economic Society, Econometrica,* 12, pp.206-214.

Cowles, A. (1933) 'Can stock market forecasters forecast?', *Journal of Economic society, Econometrica,* 1, pp.309-324.

Cowles, A. and Jones, H. (1937) 'Some a posteriori probabilities in stock market action', *Econometrica,* 5 (3), pp. 280-294.

Craig, S. and Corkery, M. (2009) 'Deal Journal: Goldmans' analysts take one for the team', *In press, Wall Street Journal,* August.

Daniel, K. and Moskowitz, T. (2013) 'Momentum Crashes', available [online] at https://www0.gsb.columbia.edu/mygsb/faculty/research/pubfiles/4607/mom_crash.pdf.

Daniel, K. D., Hirshleifer, D. and Subrahmanyam, A., (1998) 'Investor psychology and security market under and over-reactions', *Journal of Finance,* 53(6), pp. 1839–1886.

Das, S., Levine, C. and Sivaramakrishnan, K. (1998) 'Earnings predictability and bias in analysts' earnings forecasts', *The Accounting Review,* 73(2), pp. 277-294.

De Bondt, W. and Forbes, W. (1999) 'Herding in analyst earnings forecasts: Evidence from the United Kingdom', *European Financial Management,* 5(2), pp. 143-163.

De Bondt, W.F., and Thaler, R. (1985) ‘Does the stock market overreact?’, *Journal of Finance,* 40(3), pp. 793-805.

Dechow, P., Hutton, A. and Sloan, R. (2000) ‘The relation between analysts’ forecasts of long-term earnings growth and stock performance following equity offerings’, *Contemporary Accounting Research,* 17(1), pp. 1-32.

DeLong, J. B., Shleifer, A., Summers, L. and Waldmann, R. J., (1991) ‘The survival of noise traders in financial markets’, *Journal of Business,* 64(1), pp. 1–20.

Demers, E. and Lev, B. (2001) ‘A rude awakening: Internet shakeout in 2000’, *Review of Accounting Studies,* 6(2-3), pp. 331-360.

Demir, I., Muthuswamy, J. and Walter, T. (2004) ‘Momentum returns in Australian equities: The influences of size, risk, liquidity and return computation’, *Pacific-Basin Journal of Finance,* 12(1), pp. 143-158.

Diefenback, R. (1972) ‘How good is institutional brokerage research?’, *Financial Analysts Journal,* 28, pp. 54-60.

Dimson, E. and Marsh, P. (2009) ‘An analysis of brokers and analysts unpublished forecasts UK stock returns’, *Journal of Finance,* 39(5), pp. 1257-1292.

Dische, A. (2002) ‘Dispersion in analyst forecasts and the profitability of earnings momentum strategies’, *European Financial Management,* 8(2), pp. 211-228.

Dissanike, G. (1997) ‘Do stock market investors overreact?’, *Journal of Business Finance and Accounting,* 24(1), pp. 27-50.

Doukas, J. A. and McKnight, P. J., (2005) ‘European momentum strategies, information diffusion, and investor conservatism’, *European Financial Management,* 11(3), pp. 313–38.

Doukas, J., Kim, C. and Pantzalis, C. (2005) 'The two faces of analyst coverage', *Financial Management,* 34(2), pp. 99-125.

Drew, M., Veeraraghavan, M. and Ye, M. (2007) 'Do momentum strategies work? Australian evidence', *Managerial Finance,* 33(10), pp. 772-787.

Du, D. (2008) 'The 52-week high and momentum investing in international stock indexes', *Quarterly Review of Economics and Finance,* 48(1), pp. 61-77.

Du, D. (2012) 'Momentum and behavioural finance', *Managerial Finance,* 38(4), pp. 364-379.

Dubois, M. and Dumontier, P. (2008) 'Regulating the financial analysis industry: Is the European Directive Effective?', [online] available at http://ssrn.com/abstract=1099081.

Dugar, A. and Nathan, S. (1995) 'The effect of investment banking relationships on financial analysts' earnings forecasts and investments recommendations', *Contemporary Accounting Research,* 12(1), pp. 131-160.

Durand, R., Limkriangkrai, M. and Smith, G. (2006) 'Momentum in Australia: A note', *Australian Journal of Management,* 31(2), pp. 355-364.

Dzielinsk, M. (2011) 'News sensitivity and the cross-section of stock returns', NCCR-Finrisk 719, University of Zurich, [online] available at http://www.zora.uzh.ch.

Easterwood, J. and Nutt, S. (1999) 'Inefficiency in analysts' earnings forecasts: Systematic misreaction or systematic optimism?', *Journal of Finance,* 54(5), pp. 1777-1797.

Elton, J., Gruber, M. and Grossman, S. (1986) 'Discrete expectational data and portfolio performance', *Journal of Finance,* 41(3), pp. 699-713.

Ertimur, Y., Mayew, W. and Stubben, S. (2011) 'Analyst reputation and the issuance of disaggregated earnings forecasts to I/B/E/S', *Review of Accounting Studies,* 16(1), pp. 29-58.

Fama, E. (1970) 'Efficient capital markets: A review of theory and empirical work', *Journal of Finance,* 25(2), pp. 383-417.

Fama, E. F (1965) 'The Behaviour of Stock Market Prices', *Journal of Business,* 38, pp. 34-105.

Fang, L. and Yasuda, A. (2014) 'Are stars' opinion worth more? The relation between analyst reputation and recommendation values', *Journal of Financial Services Research,* 46(3), pp.235-269.

Fischer, B. and Scholes, M. (1973) 'The pricing of options and corporate liabilities', *Journal of the Political Economy,* 81(3), pp. 637-654.

Fong, W.M., Wong, W.K. and Lean, H.H. (2005) 'International momentum strategies: a stochastic dominance approach', *Journal of Financial Markets,* 8(1), pp. 89-109.

Forbes, W. (1996) 'Picking winners? A survey of the mean reversion and overreaction of stock prices literature', *Journal of Economic Surveys,* 10(2), pp. 123-158

Forbes, W. (2013) 'No conflict, no interest: On the economics of conflicts of interest faced by analysts', *European Journal of Law and Economics,* 35(3), pp. 327-348.

Forbes, W. and Igboekwu, A. (2015) 'The explanatory power of representative agent earnings momentum models', *Review of Quantitative Finance and Accounting,* 44(3), pp. 473-492.

Forner, C. and Joaquin, M. (2003) 'Contrarian and momentum strategies in the Spanish stock market', *European Financial Management,* 9(1), pp. 67-88.

Foster, G., Olsen, C. and Shevlin, T. (1984) ‘Earnings release, anomalies and the behaviour of security returns’, *The Accounting Review,* 59(4), pp. 574-603.

Fountas, S. and Segredakis, K. (2002) ‘Emerging stock market return seasonalities: the January effect and the tax-loss selling hypothesis’, *Applied Financial Economics,* 12(4), pp. 291-299.

Francis, J. and Philbrick, D. (1993) ‘Analysts’ decisions as products of multi-task environment’, *Journal of Accounting Research,* 31(1), pp. 216-230.

Francis, J., LaFond, R., Olsson, P. and Schipper, K. (2005) ‘The market pricing of accruals quality’, *Journal of Accounting and Economics,* 39(2), pp. 295-327.

Fraulo, P. and Nguyen, J. (2009) ‘Do industries explain momentum?-A replication of Moskowitz and Grinblatt 1999’, available [online] at http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.319.6121.

Frazzini, A. (2006) ‘The disposition effect and underreaction to news’, *Journal of Finance,* 61(4), pp. 2017-2046.

Frey, S. and Herbst, P. (2014) ‘The influence of buy-side analysts on mutual fund trading’, *Journal of Banking and Finance,* 49(12), pp. 442-458.

Fu, H.P. and Wood, A. (2010) ‘Momentum in Taiwan: Seasonality matters!’, *Applied Economic Letters,* 17(13), pp. 1247-1253.

Fuertes, A.M., Miffre, J. and Tan, W.H. (2009) ‘Momentum profits, nonnormality risks and the business cycle’, *Applied Financial Economics,* 19(12), pp. 935-953.

Galariotis, E. (2014) ‘Contrarian and momentum trading: A review of the literature’, *Review of Behavioural Finance,* 6(1), pp. 63-82.

Galariotis, E., Holmes, P. and Ma, C.X. (2007) 'Contrarian and momentum profitability revisited: Evidence from the London Stock Exchange 1964-2005', *Journal of Multinational Financial Management,* 17(5), pp. 432-447.

Galariotis, E.C. (2010) 'What should we know about momentum investing? The case of the Australian Security Exchange', *Pacific Basin Finance Journal,* 18(4), pp. 369-389.

Geczy, C. and Samonov, M. (2013) '2012 years of price momentum (The world's longest backtest: 1801-2012)', [online] available at http://ssrn.com/abstract=2292544

Geczy, C., Musto, D. and Reed, A. (2002) 'Stocks are special too: An analysis of equity lending market', *Journal of Financial Economics,* 66(2-3), pp. 241-269.

Genesove, D. and Mayer, C. (2001) 'Nominal loss aversion and sell behaviour: Evidence from the housing market', *Quarterly Journal of Economics,* 116(4), pp. 1233-1260.

George, T.J. and Hwang, C. (2004) 'The 52-week high and momentum investing', *Journal of Finance,* 59(5), pp. 2145-2176.

Gervais, S. and Odean, T. (2001) 'Learning to be overconfident', *Review of Financial Studies,* 14(1), pp. 1-27.

Giannikos, C. and Ji, X. (2007) 'Industry momentum at the end of the 20^{th} Century', *International Journal of Business and Economics,* 6, pp. 29-46.

Gilovich, T., Vallone, R. and Tversky, A. (1985) 'The hot hand in basketball: On the misperception of random sequences', *Cognitive Psychology,* 17(3), pp. 295-314.

Givoly, D. and Lakonishok (1979) 'The information content of financial analysts' forecasts of earnings: Some evidence on semi-strong efficiency', *Journal of Accounting and Economics,* 1(3), pp.165-185.

Givoly, D. and Lakonishok (1984) ‘The quality of analysts’ forecasts of earnings’, *Financial Analysts Journal,* Sept-Oct, pp. 40-47.

Givoly, D. and Lakonishok, J. (1979) ‘The information content of financial analysts’ earnings forecasts’, *Journal of Accounting and Economics,* 1(3), pp. 165-185.

Glaser, M. and Weber, M. (2003) ‘Momentum and turnover: Evidence from the German stock market’, *Schmalenbach Business Review,* 55(2), pp. 108-135.

Goff, D., Hulbert, H., Keasler, T. and Walsh, J. (2008) ‘Isolating the information content of equity analysts recommendation changes post Reg FD’, *Financial Review,* 43(2), pp. 303-321.

Gong, Q., Liu, M. and Liu, Q. (2015) ‘Momentum is really short-term momentum’, *Journal of Banking and Finance,* 50, pp, 169-182.

Graham, B. and Dodd, D. (1940) ‘Security Analysis: Principles and Technique’, McGraw-Hill Company, New York.

Green, T. (2006) ‘The value of client access to analyst recommendations’, *Journal of Financial and Quantitative Analysis,* 41(1), pp. 1-24.

Griffin J, Xiuqing, JI., and Martin S (2003) ‘Momentum investing and Business Cycle Risk: Evidence from Pole to Pole’, *Journal of Finance,* 58(6), pp. 2515-2549.

Griffin, J.M., Harris, J.H. and Topaloglu, S. (2003) ‘The dynamics of institutional and individual trading’, *Journal of Finance,* 58(6), pp. 2285-2320.

Grinblatt, M. and Han, B. (2005) ‘Prospect theory, mental accounting and momentum’, *Journal of Financial Economics,* 78(2), pp. 311-339.

Grinblatt, M. And Moskowitz, T. (2004) 'Predicting stock price movements from past returns: The role of consistency and tax-loss selling', *Journal of Financial Economics,* 71(3), pp. 541-579.

Grinblatt, M., Titman, S and Wermers, R. (1995) 'Momentum investing strategies, portfolio performance and herding: A study of mutual fund behaviour', *American Economic Review,* 85, pp. 1088-1105.

Grobys, K. (2014) 'Momentum in global equity markets in times of troubles: Does the economic state matter?', *Economics Letters,* 123, pp. 100-103.

Grossman, S.J. and Stiglitz, J. (1980) 'On the impossibility of informationally efficient markets', *American Economic Review,* 70, pp. 393-408.

Groth, J., Lewellen, W., Schlarbaum, G. and Lease, R. (1979) 'An analysis of brokerage house securities recommendations', *Financial Analysts Journal,* 35, pp. 32-40.

Groysberg, B., Healy, P. and Maber, D. (2011) 'What drives sell-side analyst compensation at high-status investment banks?', *Journal of Accounting Research,* 49(4), pp. 969-1000.

Grundy, B.D and Martin J.S. (2001) 'Understanding the nature of the risks and the source of the rewards to momentum investing', *Review of Financial Studies,* 14(1), pp. 29-78.

Haigh, M. and List, J. (2005) 'Do professional traders exhibit myopic loss aversion? An experimental analysis', *Journal of Finance,* 60(1), pp. 523-534.

Hameed, A. and Kusnadi, Y. (2002) 'Momentum strategies: Evidence from Pacific-basin stock markets', *Journal of Financial Research,* 25(3), pp. 383-397.

Hammami, Y. (2013) 'Momentum investing across economic states: evidence of market inefficiency in good times', *Applied Financial Economics,* 23(1), pp. 51-56.

Hanna, J. and Ready, M. (2005) ‘Profitable predictability in the cross section of stock returns’, *Journal of Financial Economics,* 78(3), pp. 463-505.

Hayes, R. (1998) ‘The impact of trading commission incentives on analysts’ recommendations and earnings forecast revisions’, *Journal of Accounting Research,* 35(1), pp. 193-211.

Heath, C., Hubbart, S. and Long, M. (1999) ‘Psychological factors and stock options exercise’, *Quarterly Journal of Economics,* 114, pp. 601-627.

Heflin, F., Subramanyam, K. and Zhang, Y. (2003) ‘Regulation FD and the financial information environment: Early evidence’, *Accounting Review,* 78(1), pp. 1-37.

Heidle, H.G. and Li, X. (2005) ‘Information leakage and opportunistic behaviour before analyst recommendations: An analysis of the quoting behaviour of NASDAQ market makers’, AFA San Diego Meetings, [online] available at: http://ssrn.com/abstract=423840.

Heilman, R., Crisan, L.G., Houser, D., Miclea, M. and Miui, A.C. (2010) ‘Emotion regulation and decision making under risk and uncertainty’, *Emotion,* 10(2), pp. 257-265.

Hendricks, D., Patel, J. and Zeckhauser, R. (1993) ‘Hot-hands in mutual funds: Short-run persistence of relative performance’, 1974-1988, *Journal of Finance,* 48(1), pp. 93-130.

Herberger, T., Kohlert, D., and Ohler, A. (2009) ‘Momentum and Industry dependence: An analysis of the Swiss stock market’, *Journal of Asset Management,* 11(6), pp. 391-400.

Hilary, G. and Hsu. C. (2013) ‘Analyst forecast consistency’, *Journal of Finance,* 68(1), pp. 271-297.

Hirshleifer, D., Subrahmanyam, A. and Titman, S. (2006) ‘Feedback and the success of irrational investors’, *Journal of Financial Economics,* 81(2). Pp. 311-338

Hoffmann, A, Post., T. and Pennings, J. (2013) ‘Individual investor perceptions and behaviour during the financial crisis’, *Journal of Banking and Finance,* 37(1), pp. 60-74.

Hon, M. and Tonks, I. (2003) ‘Momentum in the UK Stock market’, *Journal of Multinational financial Management,* 13(1), pp. 43-70.

Hong, H. and Kubik, J. (2003) ‘Analyzing the analysts: Career concerns and biased earnings forecasts’, *Journal of Finance,* 58(1), pp. 313-351.

Hong, H. and Stein, J. (1999) ‘A unified theory of underreaction, momentum trading and overreaction in asset markets’, *Journal of Finance,* 54(6), 2413-2184.

Hong, H., Kubik, J. and Solomon, A. (2000) ‘Security analysts’ career concerns and herding of earnings forecasts’, *RAND Journal of Economics,* 31, pp. 121-144.

Hong, H., Kubik, J. and Stein, J., (2005) ‘Thy neighbor’s portfolio: Word-of-mouth effects in the holdings and trades of money managers’, *Journal of Finance,* 60(6), pp. 2801–2824.

Hong, H., Lim, T. and Stein, J. (2000) ‘Bad news travels slowly: Size, analyst coverage and the profitability of momentum strategies’, *Journal of Finance,* 55(1), pp. 265-295.

Hou, K., Karoyi, G. and Kho, B. (2011) ‘What factors drive global stock returns?’, *Review of Financial Studies,* 24, pp. 2527-2574.

Hou, T. and McKnight, P. (2004) ‘An explanation of momentum in Canadian stocks’, *Canadian Journal of Administrative Sciences,* 21(4), pp. 334-343.

Hribar, P. and McInnis, J. (2012) ‘Investor sentiment and analysts’ earnings forecast errors’, *Management Science,* 58(2), pp. 293-307

Hsu, C.Y., Yu, J. and Wen, S.Y. (2013) ‘The analysts’ forecast of IPO firms during the global financial crisis’, *International Journal of Economics and Financial Issues,* 3(3), pp. 673-682.

Hsu, H., Reed, A. and Rocholl, J. (2010) ‘The new game in town: Competitive effects of IPOs’, *Journal of Finance,* 65(3), pp. 495-528.

Hu, J.W.S. and Chen, Y.C. (2011) ‘The performance of momentum investment strategies: An International Examination of stock markets’, *International Journal of Management,* 28(4), p.165.

Hu, J.W.S. and Chen, Y.C. (2011) ‘The performance of momentum investment strategies: An international examination of stock markets’, *International Journal of Management,* 28(4), pp. 165-176.

Hurn, A. and Pavlov, V. (2003) ‘Momentum in Australian stock returns’, *Australian Journal of Management,* 28(2), pp. 141-155.

Irvine, P. (2004) ‘Analysts’ forecasts and brokerage-firm trading’, *Accounting Review,* 79(1), pp. 125-150.

Irvine, P., Lipson, M. and Puckett, A. (2007) ‘Tipping’, *Review of Financial Studies,* 20(3), pp. 741-768.

Ivkovic, Z. and Jegadeesh, N. (2004) ‘The timing and value of forecast and recommendation revisions’, *Journal of Financial Economics,* 73(3), pp. 433-463.

Jackson, A. (2005) ‘Trade generation, reputation, and sell-side analysts’, *Journal of Finance,* 60(2), pp.673–717.

Jackson, A. and Johnson, T. (2006) 'Unifying underreaction anomalies', *Journal of Business,* 79(1), pp.75-114.

Jacob, J., Rock, S. and Weber, P. (2003) 'Do analysts at independent research firms make better earnings forecasts?', *working paper,* [online] available at http://ssrn.com/abstract=434702.

Jaffe, J.F. and Mahoney, J.M. (1999) 'The performance of investment newsletters', *Journal of Financial Economics,* 53(2), pp. 289-307.

Jegadeesh, N. and Kim, N. (2010) 'Do analysts herd? An analysis of recommendations and market reactions', *The Review of Financial Studies,* 23(2), pp. 901-937.

Jegadeesh, N. and Titman, S. (1993) 'Returns to buying winners and selling losers; implications for stock market efficiency', *Journal of Finance,* 48(1), pp. 65-91.

Jegadeesh, N. and Titman, S. (2001) 'Profitability of momentum strategies: An evaluation of alternative explanations', *Journal of Finance,* 56(2), pp. 699-720.

Jian, S., Chiang, T. and Liang, X. (2012) 'Positive feedback trading activity and momentum profits', *Managerial Finance,* 38(5), pp. 508-529.

Johnson, T. (2002) 'Rational Momentum Effects', *Journal of Finance,* 57(2), pp. 585-608.

Jordan, B., Liu, M. and Wu, Q. (2012) 'Do investment banks listen to their own analysts?', *Journal of Banking and Finance,* 36, pp. 1452-1463.

Juergens, J.L. and Lindsey, L.A. (2009) 'Getting out early: An analysis of market making activity of the recommending analyst firm', *Journal of Finance,* 64(5), pp. 2327-2359.

Jung, J.H., Pae, J. and Yoo, C.Y. (2014) ‘Do analysts treat winners and losers differently when forecasting earnings’, *International Journal of Forecasting,*31(2), pp.531-549.

Kadan, O., Madureira, L., Wang, R. and Zach, T. (2009) ‘Conflicts of interest and stock recommendations: The effects of the global settlement and related regulations’, *The Review of Financial Studies,* 22(10), pp. 4189-4217.

Kahneman, D. and Tversky, A. (1972) ‘Subjective probability: a judgement of representativeness’, *Cognitive Psychology,* 3(3), pp. 430-454.

Kahneman, D. and Tversky, A. (1979) ‘Prospect theory: An analysis of decision under risk’, *Journal of Economic society, Econometrica,* 47, pp. 263-291.

Kaniel, R., Saar, G. and Titman, S. (2008) ‘Individual investor trading and stock returns’, *Journal of Finance,* 63(1), pp. 273-310.

Karolyi, G. and Kho, B.C. (2004) ‘Momentum strategies: some bootstrap tests’, *Journal of Empirical Finance,* 11(4), pp. 509-536.

Keane, M. and Runkle, D. (1998) ‘Are financial analysts’ forecasts of corporate profits rational?’, *Journal of Political Economy,* 106(4), pp. 768-805.

Keim, D. (1983) ‘Size related anomalies and stock return seasonality’, *Journal of Financial Economics,* 12(1), pp. 13-22.

Kendall, M. (1953) ‘The analysis of economic time series’, *Prices’, Journal of Royal Statistical Society,* 1(1), pp. 11-25.

Kim, M., Nelson, C. and Startz, R. (1991) ‘Mean reversion in stock prices? A reappraisal of the empirical evidence’, *Review of Economic Studies,* 58(3), pp. 515-328.

Kim, S.T., Lin, J. and Slovin, M.B. (1997) 'Market structure, informed trading and analysts' recommendations', *Journal of Financial and Quantitative Analysis,* 32(4), pp. 507-524.

Kolasinski, A. and Kothari, S. (2004) 'Investment banking and analyst objectivity: Evidence from forecasts and recommendations of analysts affiliated with M&A advisors', *Journal of Financial and Quantitative Analysis,* 43(4), pp. 817-842.

Korajczyk, R. and Sadka, R. (2004) 'Are momentum profits robust to trading costs?', *Journal of Finance,* 59(3), pp. 1039-1082.

Kothari, S.P. (2001) 'Capital markets research in accounting', *Journal of Accounting and Economics,* 31(1), pp. 105-231.

Koutmos, G. (2014) 'Positive feedback trading: A Review', *Review of Behavioural Finance,* 6(2), pp. 155-162.

Kyle, A. and Wang, F. (1997) 'Speculation duopoly with agreement to disagree: Can overconfidence survive the market test?, *Journal of Finance,* 52(5), pp. 2073-2090.

Lakonishok, J., Vishny, R.W. and Shleifer, A. (1994) 'Contrarian investment, extrapolation and risk', *Journal of Finance,* 49(5), pp. 1541-1578.

Lee, C. and Swaminathan, B. (2000) 'Price momentum and trading volume', *Journal of Finance,* 55(5), pp. 1217-1269.

Lepone, A., Leung, H. and Li, G. (2002) 'Unequal access to analyst research', *Australian Journal of Management,* 38(1), pp. 1-37.

Lepone, A., Lim, M.Y. and Wong, J.B. (2014) 'Information Leakage on analyst recommendations: Does it exist?', [online] available at www.cmcrc.com/.../1369984732

Lesmond, D. A., Schill, M.J and Zhou, C. (2004) 'The illusory nature of momentum profits', *Journal of Economics,* 7(2), pp. 349-380.

Lev, B. and Ohlson, J. (1982) 'Market-based empirical research in accounting: Review, interpretation and extension', *Journal of Accounting Research,* 20, pp. 249-322.

Levy, R.A. (1967) 'Relative strength as a criterion for investment selection', *Journal of Finance,* 22(4), pp. 595-610.

Lewellen, J. (2002) 'Momentum and autocorrelation in stock returns', *Review of Financial Studies,* 15(2), pp. 533-564.

Li, K. and Uddin, M.R. (2011) 'Role of analysts: Following momentum or creating momentum?', [online] available at http://ssrn.com/abstract=1933987.

Li, M. and Xin, Z. (2008) 'Analyst reputation, dealer affiliation and market making', *Journal of Financial Research,* 31(4), pp. 301-332.

Lim, T. (2001) 'Rationality and analysts' forecast bias', *Journal of Finance,* 56(1), pp. 369-385.

Lin, H. and McNichols, M. (1998) 'Underwriting relationships, analysts' earnings forecasts and investment recommendations', *Journal of Accounting and Economics,* 25(1), pp. 101-127.

Lintner, J. (1965) 'The valuation of risky assets and the selection of risky investments in stock portfolios and capital budgets', *The Review of Economics and Statistics,* 47(1), pp. 13-37.

Liu, L. and Zhang, L. (2008) 'Momentum Profits, Factor Pricing and Macroeconomic Risk', *Review of Financial Studies,* 21(6), pp. 2417-2448.

Liu, M., Liu, Q. and Ma, T. (2011) 'The 52 week high momentum strategy in international stock markets', *Journal of International Money and Finance,* 30(1), pp. 180-204.

Liu, Q. and Song, F. (2006) 'The rise and fall of interest stocks: Should financial analysts be blamed?' *Working paper,* School of Economics University of Hong Kong.

Liu, W., Norman, S. and Xu, X.. (1999) 'The profitability of momentum investing', *Journal of Business Finance and Accounting,* 26(9/10), pp. 1043-1091.

Ljungqvist, A., Marston, F. and Wilhelm, W. (2006) 'Competing for securities underwriting mandates: Banking relationships and analyst recommendations', *Journal of Finance,* 61(1), pp. 301-340.

Lo, A. and MacKinlay, C. (1988) 'Stock market prices do not follow random walks: Evidence from a simple specification test', *Review of Financial Studies,* 1(1), pp.41-66.

Lo, A. and MacKinlay, C. (1990) 'When are contrarian profits due to stock market overreaction?', *Review of Financial Studies,* 3(2), pp. 175-205.

Locke, P. and Mann, S. (2000) 'Do professional traders exhibit myopic loss aversion? An experimental analysis', *Journal of Finance,* 60(1), pp. 523-534.

Logue, T. And Tuttle, T. (1973) 'Brokerage house investment advice', *Financial Review,* 8(1), pp. 38-54.

Loh, R. and Mian, M. (2006) Do accurate earnings forecasts facilitate superior investment recommendations?, *Journal of Financial Economics,* 80(2), pp. 455-483.

Loh, R.K. and Mian. M. (2003) 'The quality of analysts' earnings forecasts during the Asian crisis', *Journal of Business Finance and Accounting,* 30(5), pp. 749-769.

Madura, J. and Premti, A. (2014) ‘Impact of regulatory enforcement on leakages prior to analyst recommendations’, *Financial Review,* 49(3), pp. 565-592.

Malmendier, U. and Nagel, S. (2011) ‘Depression babies: Do macroeconomic experiences affect risk trading?’, *Quarterly Journal of Economics,* 126, pp. 373-416.

Mansouri, S., Tehrani, R. and Ansari, H. (2012) ‘Momentum returns in the Tehran stock exchange: The influences of size and liquidity’, *International Business Research,* 5(11), pp. 4-43.

Markowitz, H. (1952) ‘Portfolio selection’, *Journal of Finance,* 7(1), pp. 77-91.

McInish, T., Ding, D., Pyun, C. and Wongchoti, U. (2008) ‘Short-horizon contrarian and momentum strategies in Asian Markets: An integrated analysis’, *International Review of Financial Analysis,* 17(2), pp. 312-329.

McKnight, P. and Hou, T. (2006) ‘The determinants of momentum in the United Kingdom’, *Quarterly Review of Economics and Finance,* 46(2), pp. 227-240.

McNichols, M. and O’Brien, O. (1997) ‘Self-selection and analyst coverage’, *Journal of Accounting Research,* 35, pp. 167-199.

Mehran H. and R. Stulz (2007) ‘The economics of conflicts of interest in financial institutions’, *Journal of Financial Economics,* 85(2), pp. 267-296.

Menkhoff, L. (2010) ‘Are momentum traders different? Implications for the momentum puzzle’, *Discussion paper 448,* May 2010, ISSN 0409-9962.

Menkhoff, L., Schmidt, U. And Brozynski, T. (2006) ‘The Impact of Experience on Risk Taking, Overconfidence and Herding of Fund Managers: Complementary Survey Evidence’, *European Economic Review,* 50(7), pp. 1753-1766.

Mian, A and Sufi, A. (2011) 'Consumers and the Economy, Part II: Household debt and the weak US recovery', FRBSF Economic Letter 2011, Issue January 18.

Michaely, R., Womack, K., (1999) 'Conflict of interest and the credibility of underwriter analysts' recommendations', *Review of Financial Studies,* 12(4)*,* pp. 653–686.

Michel, J.S. and Pandes, J. A. (2012) 'Why do analysts disagree?', [online] available at; http://econpapers.repec.org/paper/lvllacicr/1305.html.

Mikhail, M., Walther B. and Willis, R., (2007) 'When analysts talk, who listens?', *Accounting Review,* 82(5)*,* pp. 1227–1253.

Modigliani, F. and Miller, M. H. (1958) 'The Cost of Capital, Corporate Finance and the Theory of Investment', *American Economic Review*, 48(3), pp. 261-97.

Mohanram, P. and Sunder, S. (2006) 'How has regulation FD affected the operations of financial analysts?', *Contemporary Accounting Research,* 23(2)*,* pp. 491-525.

Mohanram, P.S and Sunder, S.V. (2006) 'How has regulation FD affected the operations of financial analysts?', *Contemporary Accounting Research,* 23(2), pp. 491-525.

Mongin, P. (1997) 'Expected utility theory', *Handbook of economic methodology,* pp.342-350, London.

Moshirian, F. (2011) 'The global financial crisis and the evolution of markets, institutions and regulation', *Journal of Banking and Finance,* 35(3)*,* pp. 6502-511.

Moshirian, F., Ng, D. and Wu, E. (2009) 'The value of analysts' recommendations: Evidence from emerging markets', *International Review of Financial Analysis,* 18(1), pp. 74-83.

Moskowitz, T. and Grinblatt, M. (1999) ‘Do industries explain momentum?’, *Journal of Finance,* 54(4), pp. 1249-1290.

Moskowitz, T., Ooi, Y. H. and Pedersen, L. H. (2012) ‘Time series momentum’, *Journal of Financial Economics,* 104(2), pp. 228-250.

Muga, L. and Santamaria, R. (2007) ‘The original stock market crisis and momentum. Some evidence for the Spanish stock market during the 1990s’, *Applied Financial Economics,* 17(6), pp. 469-486.

Muslu, V. and Xue, Y. (2013) ‘Analysts’ momentum recommendations’, *Journal of Business Finance and Accounting,* 40(3-4), pp. 438-469.

Mussweiler, T. and Schneller, K. (2003) ‘What goes up must come down- How charts influence decisions to buy and sell stocks’, *Journal of Behavioural Finance,* 4(3), pp. 121-130.

Naranjo, A. and Porter, B. (2007) ‘Including emerging markets in international momentum investment strategies’, *Emerging Markets Review,* 8(2), pp. 147-166.

Nickell, S. (1985) ‘Error correction, partial adjustment and all that: An expository note’, *Oxford Bulletin of Economics and Statistics,* 47(2), pp. 119-129.

Niehaus, G. and Zhang, D. (2010) ‘The impact of sell-side analyst research coverage on an affiliated broker’s market share of trading volume’, *Journal of Banking and Finance,* 34(4), pp. 776-787.

Nijman, T., Swinkles, L. and Verbeek, M. (2004) ‘Do countries or industries explain momentum in Europe?’, *Journal of Empirical Finance,* 11(4), pp. 461-481.

Nofsinger, J. and Sias, R. (1999) ‘Herding and feedback trading by institutional and individual investors’, *Journal of Finance,* 54(6), pp. 2263-2295.

Novy-Marx, R. (2012) 'Is momentum really momentum?', *Journal of Financial Economics,* 103, pp. 429-453.

Nutt, S., Easterwood, J. and Easterwood, C. (1999) 'New evidence on serial correlation in analyst forecast errors', *Financial Management,* 28(4), pp. 106-117.

O'Brien, P, McNichols, M. and Lin, H. (2005) 'Analysts impartiality and investment banking relationships', *Journal of Accounting Research,* 43(4), pp. 623-650.

O'Brien, P., and Tian, Y. (2006) 'Financial analysts' role in the 1996-2000 Internet bubble', *Working paper.*

O'Keeffe, C. and Gallagher, L.A. (2014) 'Momentum in Irish stocks: evidence from the credit crisis', *Applied Economics Letters,* 21(11), pp. 717-722.

Okunev, J. and White, D. (2003) 'Do momentum-based strategies still work in foreign currency markets?', *Journal of Financial and Quantitative Analysis,* 38(2), pp. 425-447.

Oppenheimer, D. and Monin, B. (2009) 'The retrospective gambler's fallacy: Unlikely events, constructing the past, and multiple universes', *Judgement and Decision Making,* 4(5), pp. 326-334.

Pan, M.S., Liano, K. and Huang, G. (2004) 'Industry momentum strategies and autocorrelations in stock returns', *Journal of Empirical Finance,* 11(2), pp. 185-202.

Papaioannou, M., Park, J., Pihlman, J. and van der Hoorn, H. (2013) 'Pro-cyclical behaviour of institutional investors during the recent financial crisis, causes, impacts and challenges', *IMF working paper,* [online] available at https://www.imf.org/external/pubs/ft/wp/2013/wp13193.pdf

Pasquariello, P. (2014) 'Prospect theory and market quality', *Journal of Economic Theory,* 149, pp. 276-310.

Pástor,L and Stambaugh, F. (2003), ‘Liquidity risk and expected stock returns’, *Journal of Political Economy,* 111(3), pp. 642-685.

Patro, D.K. and Wu, Y. (2004) ‘Predictability of short-horizon returns in international equity markets’, *Journal of Empirical Finance,* 11(4), pp. 553-584.

Phua, V., Chan, H., Faff, R. and Hudson, R. (2010) ‘The influence of time, seasonality and market states on momentum: Insights from the Australian stock market’, *Applied Financial Economics,* 20(20), pp. 1547-1563.

Pilbeam, K. (1998). International finance (2nd ed.). Palgrave.

Poteshman, A. (2001) ‘Underreaction, overreaction, and increasing misreaction to information in the options market’, *Journal of Finance,* 56(3), pp. 851-876.

Qian, H. (2009) ‘Time variation in analyst optimism: An investor sentiment explanation’, *Journal of Behavioural Finance,* 10(3), pp. 182-193.

Rabin, M. (2002) ‘Inference by believers in the law of small numbers’, *Quarterly Journal of Economics,* 117(3), pp. 775-816.

Rabin, M. and Vayanos, D. (2010) ‘The gambler’s and hot-hand fallacies: Theory and applications’, *Review of Economic Studies,* 77(2), pp. 730-778

Ramiah, V., Cheng, Y., Orriols, J., Naughton, T. and Hallahan, T. (2011) ‘Contrarian investment strategies work better for dually-traded stocks: Evidence from Hong Kong’, *Pacific-Basin Finance Journal,* 19(1), pp. 140-156.

Rey, D. and Schmid, M. (2007) ‘Feasible momentum strategies: Evidence from the Swiss stock market’, *Financial Markets and Portfolio Management,* 21(3). Pp. 325-352.

Rouwenhorst, G. (1999) ‘Local return factors and turnover in emerging markets’, *Journal of Finance,* 54, pp. 1439-1464.

Rouwenhorst, K., (1998) 'International Momentum Strategies', *Journal of Finance,* 53(1), pp. 267–284.

Rozeff, M. and Kinney, W. (1976) 'Capital market seasonality: The case of stock returns', *Journal of Financial Economics,* 2(4), pp. 379-402.

Ryan, P. and Curtin, R. (2006) 'Profitability of price momentum strategies: Surprising evidence from Pacific-Basin countries', *The Journal of Investing,* 15(4), pp. 38-45.

Ryan, P. and Taffler, R. (2006) 'Do brokerage houses add value? The market impact of UK sell-side analyst recommendation changes', *The British Accounting Review,* 38(4), pp. 371-386.

Sadka, R. (2005) 'Momentum and post-earnings-annoucement-drifts anomalies: The role of Liquidity risk', *Journal of Financial Economics,* 80(2), pp. 309-349.

Safieddine, A. and Sonti, R. (2007) 'Momentum and industry growth', *Review of Financial Economics,* 16(2), pp. 203-215.

Savor, P.G. (2012) 'Stock returns after major price shocks: The impact of information', *Journal of Financial Economics,* 106(3), pp. 635-659.

Schneider, P. and Gaunt, C. (2012) 'Price and earnings momentum in Australian stock returns', *Accounting and Finance,* 52(2), pp. 495-517.

Scowcroft, A. and Sefton, J. (2005) 'Understanding momentum', *Financial Analysts Journal,* 61(2), pp. 64-82.

Sewell, M. (2010) 'Behavioural finance', [online] available at http://www.behaviouralfinance.net/behavioural-finance.pdf.

Sharpe, W. (1963) 'A simplified model for portfolio analysis', *Management Science,* 9(2), pp. 277-293.

Sharpe, W. (1964) 'Capital asset prices: A theory of market equilibrium under conditions of risk', *Journal of Finance,* 19(3), pp.425-442.

Shefrin, H. (2000) '*Beyond greed and fear; Understanding behavioural finance and the psychology of investing'*, Harvard Business School Press, Boston.

Shefrin, H. (2005) '*A behavioural approach to asset pricing theory'*, Burlington, Elsevier.

Shefrin, H. and Statman, M. (1985) 'The disposition of sell winners too early and ride losers too long: Theory and evidence', *Journal of Finance,* 40(40), pp. 777-790.

Shi, J., Chiang, T. and Liang, X. (2012) 'Positive-feedback trading activity and momentum profits', *Managerial Finance,* 38 (5), pp. 508-529.

Shi, J., Chiang, T.C. and Liang, X. (2012) 'Positive-feedback trading activity and momentum profits', *Managerial Finance,* 38(5), pp. 508-529.

Shiller, R. (2000) '*Irrational exuberance',* Princeton University Press, Princeton, New Jersey.

Shu, T. (2009) 'Does positive feedback trading by institutions contribute to stock return momentum?', [online] available at http://ssrn.com/abstract=831364

Shynkevich, A. (2013) 'Time-series momentum as an intra- and inter-industry effect: Implications for market efficiency', *Journal of Economics and Business,* 69, pp. 64-85.

Sias, R., Starks, L. and Titman, S. (2001) 'The price impact of institutional trading', [online] available at hhtp://ssrn.com/abstract=283779.

Sidhu, B. and Tan, H.C. (2011) 'The performance of equity analysts during the global financial crisis', *Australian Accounting Review,* 21(1), pp. 32-43.

Siganos, A. (2010) ‘Can small investors exploit the momentum effect?’, *Financial markets and portfolio management*, 24(2), pp. 171-192.

Siganos, A. and Chelley-Steeley, P. (2006) ‘Momentum profits following bull and bear markets’, *Journal of Asset Management,* 6(5), pp. 381-389.

Smith, R. and Grocer, S. (2012) ‘Citi analyst lures hot internet IPOs’, *Wall Street Journal, European Edition,* Jan 5th 2012.

So, E.C. (2013) ‘A new approach to predicting analyst forecast errors: Do investors overweight analyst forecasts?’, *Journal of Financial Economics,* 108(3), pp. 615-640.

Statman, M. (1999) ‘Behavioural finance: Past battles and future engagements’, *Financial Analysts Journal*, 55(6), pp.18-27.

Stickel, S. (1995) ‘The anatomy of the performance of buy and sell recommendations’ *Financial Analysts Journal,* 51(5), pp. 25-39.

Strahilevitz, M., Odean, T. and Barber, B. (2011) ‘Once burned, twice shy: How naive learning, counterfactuals and regret affect the repurchase of stocks previously sold’, *Journal of Marketing Research,* 48(SPL), pp. 102-120.

Su, D. (2011) ‘An empirical analysis of industry momentum in Chinese stock markets’, *Emerging Markets Finance and Trade,* 47(4), pp. 4-27.

Swinkles, L. (2002) ‘International industry momentum’, *Journal of Asset Management,* 3(2), pp. 124-141.

Swinkles, L. (2004) ‘Momentum Investing: A survey’, *Journal of Asset Management,* 5(2), pp. 120-143.

Thaler, R. (1999) ‘The end of behavioural finance’, *Financial Analysts’ Journal,* 55 (6), pp. 12-17.

Thomas, J. and Zhang, F. (2008) ‘Overreaction to intra-industry information transfers?’, *Journal of Accounting Research,* 46(4), pp. 909-940.

Treffers, T., Koellinger, P. and Picot, A. (2012) ‘In the mood for risk? A random assignment experiment addressing the effects of moods on risk preferences’, [online] available at http://ssrn.com/abstract=2156782.

Tvede, L. (1999) ‘*The Psychology of Finance’,* Wiley, New York.

Tversky, A. and Kahneman, D. (1971) ‘Belief in the law of small numbers’, *Psychological Bulletin,* 76(2), pp. 105-110.

Tversky, A. and Kahneman, D. (1974) ‘Judgment under uncertainty: Heuristics and biases’, *Science*, 185(4157), pp. 1124-1131.

van der Hart, J., Slagter, E., and van Dijk, D. (2003) ‘Stock selection strategies in emerging markets’, *Journal of Empirical Finance,* 10(1), pp. 105-132.

van Dijk, R. and Huibers, F. (2002) ‘European price momentum and analysts behaviour’, *Financial Analysts Journal*, 58 (2), pp. 96-105.

Vayanos, D. (1998) ‘Transaction costs and asset prices: A dynamic equilibrium model’, *Review of Financial Studies,* 11(1), pp. 1-58.

Vayanos, D. and Woolley, P. (2013) ‘An institutional theory of momentum and reversal’, *Review of Financial Studies,* 26(5), pp. 1087-1145.

Vega, C. (2004) ‘Are investors overconfident?’, Working paper, University of Rochester.

Von Neumann, J. and Morgenstern, O. (1944) ‘*Theory of games and economic behaviour*’, Princeton, Princeton University Press, New Jersey.

Wang, K. and Xu, J. (2015) 'Market volatility and momentum', *Journal of Empirical Finance,* 30, pp. 79-91.

Welch, I. (2000) 'Herding among security analysts', *Journal of Financial Economics,* 58(3), pp. 369-396.

Womack, K. (1996) 'Do brokerage analysts' recommendations have investment value?', *Journal of Finance,* 51(1), pp. 137-167.

Wooolridge, J.M. (2013) 'Introductory econometrics: A modern approach', (5^{th} edition), South-Western, Cengage Learning, USA.

Xiang, J., He, J. and Cao, M. (2002) 'Continuous overreaction, insiders trading activities and momentum strategies', *Journal of Multinational Financial Management,* 12(4), pp. 429-449.

Xu, N., Chan, K.C, Jiang, X. and Yi, Z. (2013) 'Do star analysts know more firm-specific information? Evidence from China', *Journal of Banking and Finance,* 37(1), pp. 89-102.

Zhang, X.F. (2006) 'Information uncertainty and stock returns', *Journal of Finance,* 61(1), pp. 105-136.

Zhang, Y. (2008) 'Analysts' responsiveness and market underreaction to earnings announcements', *Journal of Accounting and Economics,* 46(1), pp. 201-215.

Appendix A-International evidence of momentum

Author(s)	Strategy	Country/Index	Time period
Alwathaninani (2012)	Individual	United States	1964-2008
Antoniou *et al.* (2007)	Individual	France, Germany, United Kingdom	1977-2002
Bird and Whitaker (2003)	Individual	Germany, Italy, France, the Netherlands, Spain, Switzerland, United Kingdom.	1990-2002
Chan *et al.* (2000)	Individual	Australia, Austria, Belgium, Canada, Denmark, France, Germany, Hong Kong, South Korea, Italy, Japan, the Netherlands, Norway, South Africa, Spain, Singapore, Switzerland, United Kingdom, United States, Thailand, Taiwan, Malaysia, Indonesia.	1980-1995
Chelley-Steely and Siganos (2006)	Individual	United Kingdom	1975-2001
Demir *et al.* (2004)	Individual	Australian.	1973-1988
Doukas and Mcknight (2005)	Individual	Austria, Belgium, Denmark, Finland, France, Germany, Italy, the Netherlands, Norway, Spain, Sweden, Switzerland, United Kingdom.	1988-2001
Drew and Ye (2004)	Individual	Australian.	1988-2002
Galariotis *et al.* (2007)	Individual	United Kingdom.	1965-2005
George and Hwang (2004)	Industry	United States	1963-2001

Glaser and Weber (2003)	Individual	Germany.	1988-2001
Grundy and Martin (2001)	Individual	United States.	1926-1995
Hon and Tonks (2003)	Individual	United Kingdom.	1955-1996
Hurn and Pavlov (2003)	Individual	Australian.	1990-2001
Jegadeesh and Titman (1993)	Individual	United States.	1965-1989
Liu *et al*. (2011)	Individual	Australia, Austria, Belgium, Canada, Denmark, France, Germany, Hong Kong, Italy, Spain, the Netherlands, Norway, Russia, Singapore, South Korea, Spain, Sweden, Switzerland, Taiwan, United Kingdom.	1975-2006
McInish *et al.* (2008)	Individual	Japan, Hong Kong, Taiwan, Korea, Malaysia, Thailand, Singapore.	1999-2000
Moskowitz and Grinblatt (1999)	Industry	United States	1963-1995
Muga and Santamaria (2007)	Individual	Spain	1997-2004
Naranjo and Porter (2007)	Individual	Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Italy, Japan, Luxembourg, the Netherlands, New Zealand, Norway, Singapore, Spain, Sweden, Switzerland, United Kingdom, United States. Argentina, Brazil, Chile, Greece, India, Indonesia, Israel, Korea, Malaysia, Mexico, Philippines, Poland, Portugal, Russia, South Africa, Taiwan, Thailand, Turkey.	1990-2004
O'Keeffe and Gallagher (2014)	Individual	Ireland	1989-2012
Rouwenhorst (1998)	Individual	Austria, Denmark, France, Germany, Italy, the Netherlands, Norway, Spain, Sweden, Switzerland,	1980-1995

		United Kingdom.	
Rouwenhorst (1999)	Individual	Argentina, Brazil, Chile, Colombia, Greece, Indonesia, India, Jordan, Korea, Malaysia, Mexico, Nigeria, Pakistan, Nigeria, Portugal, Taiwan, Thailand, Turkey, Venezuela, Zimbabwe.	1975-1997
Siganos (2010)	Individual	United Kingdom.	1975-2001
van der Hart *et al.* (2003)	Individual	Argentina, Brazil, Chile, China, Colombia, Czech Republic, Egypt, Greece, Hungry, India, Indonesia, Jordan, Korea, Malaysia, Mexico, Morocco, Nigeria, Pakistan, Peru, Philippines, Poland, Portugal, Russia, Slovakia, South Africa, Sri Lanka, Taiwan, Thailand, Turkey, Venezuela, Zimbabwe.	1985-1999
van Dijk and Huibers (2002)	Individual	Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom.	1987-1999

Appendix B-Momentum returns global financial crisis period (Individual)

Rank Period (months)		Hold period (Months) 3	6	9	12	18	24
3	W	0.003	0.009	0.015	0.021	0.032	0.056
	L	0.008	0.009	0.017	0.011	0.024	0.026
	W-L	-0.005	0.000	-0.002	0.010	0.007	0.032***
		(0.87)	(0.00)	(0.28)	(1.08)	(0.61)	(2.05)
6	W	0.001	-0.000	0.008	0.009	0.018	0.025
	L	0.011	0.007	0.019	0.016	0.021	0.020
	W-L	-0.010***	-0.008	-0.012***	-0.008	-0.003	0.005
		(2.09)	(1.20)	(1.93)	(0.99)	(0.36)	(0.39)
9	W	-0.000	0.006	0.003	0.016	0.010	0.020
	L	-0.000	0.001	0.002	0.003	0.007	0.016
	W-L	0.000	0.005	0.005	0.002	0.003	0.004
		(0.15)	(1.49)	(1.42)	(0.36)	(0.42)	(0.35)
12	W	0.005	0.004	0.003	0.002	0.005	0.003
	L	0.007	0.006	0.003	0.004	0.010	0.009
	W-L	-0.003	-0.002	-0.003	-0.002	-0.005	-0.006
		(0.99)	(0.40)	(0.93)	(0.36)	(1.46)	(1.09)
18	W	-0.000	-0.000	0.003	0.005	0.000	0.002
	L	0.002	-0.000	0.002	0.001	0.006	0.002
	W-L	-0.002***	0.000	0.001	0.004	-0.007	0.000
		(2.38)	(0.02)	(0.55)	(0.81)	(0.86)	(0.05)

*significant at 1% level
** significant at 5% level
***significant at 10% level

Appendix C-Momentum returns Internet bubble period (Individual)

		Hold period (Months)					
Rank Period (months)		**3**	**6**	**9**	**12**	**18**	**24**
3	**W**	-0.001	0.008	0.012	0.019	0.029	0.014
	L	0.007	-0.009	-0.019	-0.028	-0.026	-0.005
	W-L	-0.002	0.017	0.031*	0.046*	0.054*	0.020
		(0.49)	(2.74)	(4.05)	(5.06)	(4.73)	(1.57)
6	**W**	0.001	0.008	0.008	0.015	0.013	0.010
	L	-0.006	-0.006	-0.013	-0.012	-0.007	0.004
	W-L	0.007	0.014*	0.021*	0.27*	0.021**	0.015
		(1.71)	(3.33)	(4.35)	(4.76)	(2.47)	(1.25)
9	**W**	0.000	-0.002	-0.000	-0.001	-0.002	-0.009
	L	-0.001	-0.001	-0.006	0.007	0.003	-0.001
	W-L	0.001	-0.001	0.005	0.008	0.002	-0.008
		(0.19)	(0.27)	(1.07)	(1.07)	(0.17)	(0.70)
12	**W**	-0.003	-0.001	0.002	0.003	-0.005	-0.004
	L	-0.001	-0.004	-0.010	-0.010	-0.001	0.000
	W-L	-0.002	0.003	0.011***	0.012***	-0.004	-0.004
		(0.74)	(0.75)	(1.97)	(2.05)	(0.32)	(0.41)
18	**W**	0.001	0.001	0.001	0.002	-0.007	0.007
	L	-0.004	-0.002	-0.003	-0.004	-0.001	-0.000
	W-L	0.005	0.003	0.005	0.005	-0.006	0.007
		(1.77)	(0.67)	(0.95)	(0.78)	(0.54)	(1.67)

*significant at 1% level
** significant at 5% level
***significant at 10% level

Appendix D-Momentum returns global financial crisis period (Industry)

		Hold period (Months)					
Rank Period (months)		**3**	**6**	**9**	**12**	**18**	**24**
3	**W**	-0.003	0.000	0.004	0.002	0.004	0.015
	L	0.005	0.005	0.003	0.007	0.009	0.009
	W-L	-0.008	-0.005	0.001	-0.005	-0.005	0.005
		(1.51)	(0.62)	(0.07)	(0.39)	(0.37)	(0.39)
6	**W**	-0.000	0.003	0.005	0.003	0.003	0.009
	L	0.005	0.005	0.008	0.003	0.003	-0.000
	W-L	-0.005	0.002	-0.003	0.000	0.000	0.009
		(1.25)	(0.29)	(0.41)	(0.05)	(0.29)	(0.87)
9	**W**	0.002	0.006	0.003	-0.001	0.003	0.002
	L	-0.002	-0.003	0.001	0.001	-0.005	0.006
	W-L	0.004	0.009***	0.002	-0.003	-0.002	-0.003
		(1.57)	(2.03)	(0.54)	(0.46)	(0.37)	(0.38)
12	**W**	0.002	0.002	0.001	0.001	0.010	0.008
	L	0.005	0.002	0.001	-0.001	-0.003	-0.002
	W-L	-0.003	0.000	-0.000	-0.000	0.013	0.009
		(0.83)	(0.09)	(0.04)	(0.01)	(1.79)	(1.25)
18	**W**	0.000	0.001	-0.001	-0.003	0.001	-0.003
	L	0.000	-0.005	-0.002	-0.004	-0.008	-0.010
	W-L	0.000	0.006	0.002	0.002	0.009**	0.008***
		(0.06)	(1.55)	(0.45)	(0.32)	(5.83)	(2.41)

*significant at 1% level
** significant at 5% level
***significant at 10% level

Appendix E-Momentum returns Internet bubble period (Industry)

		Hold period (Months)					
Rank Period (months)		**3**	**6**	**9**	**12**	**18**	**24**
3	**W**	-0.001	0.004	-0.001	0.003	-0.003	-0.009
	L	0.002	-0.004	-0.001	-0.012	-0.016	-0.016
	W-L	-0.003	0.008	0.000	0.015***	0.012	0.007
		(1.06)	(1.62)	(0.05)	(1.82)	(1.28)	(0.59)
6	**W**	-0.000	0.002	-0.002	0.001	-0.004	-0.010
	L	-0.006	-0.007	-0.008	-0.011	-0.016	-0.017
	W-L	0.005***	0.009**	0.006	0.012	0.011***	0.007
		(2.02)	(2.30)	(1.07)	(1.85)	(1.45)	(0.78)
9	**W**	0.001	0.002	0.000	0.001	-0.006	-0.006
	L	-0.002	-0.002	-0.002	-0.004	0.001	-0.001
	W-L	0.003	0.004	0.002	0.005	-0.007	-0.005
		(1.26)	(1.19)	(0.43)	(0.90)	(1.06)	(0.64)
12	**W**	0.001	0.001	0.001	0.001	-0.002	-0.002
	L	-0.001	0.000	-0.004	-0.005	-0.005	0.004
	W-L	0.002	0.001	0.005	0.006	0.003	0.006
		(0.81)	(0.14)	(1.00)	(1.19)	(0.42)	(0.63)
18	**W**	0.001	0.003	0.002	0.004	0.001	-0.001
	L	-0.001	-0.002	-0.003	-0.003	-0.000	0.003
	W-L	0.002	0.005	0.005**	0.007	0.001	-0.004
		(1.14)	(1.87)	(3.12)	(3.13)	(0.47)	(1.04)

*significant at 1% level
** significant at 5% level
***significant at 10% level

Appendix F-Sharpe Ratios

Rank/hold combination	1995-2015 Individual	1995-2015 Individual *skip strategy*	1995-2015 Industry	1995-2015 Industry *skip strategy*	Global crisis period Individual	Global crisis period Industry	Internet Bubble Individual	Internet Bubble Industry
3/3	0.01	0.24	0.14	0.33	-0.16	-0.28	-0.08	-0.19
3/6	0.24	0.40	0.33	0.36	0.00	-0.12	0.50	0.29
3/9	0.27	0.42	0.26	0.32	-0.06	0.01	0.75	0.01
3/12	0.47	0.47	0.37	0.31	0.22	-0.08	0.96	0.34
3/18	0.43	0.49	0.19	0.16	0.13	-0.08	0.93	0.25
3/24	0.40	0.45	0.26	0.26	0.45	0.09	0.32	0.12
6/3	0.16	0.18	0.42	0.32	-0.57	-0.35	0.44	0.52
6/6	0.34	0.40	0.57	0.40	-0.33	0.08	0.86	0.59
6/9	0.74	0.52	0.52	0.43	-0.55	-0.12	1.16	0.28
6/12	0.61	0.33	0.57	0.37	-0.28	0.01	1.32	0.51
6/18	0.51	0.32	0.57	0.36	-0.11	0.09	0.71	0.42
6/24	0.30	0.19	0.50	0.44	0.12	0.27	0.37	0.23
9/3	-0.09	0.05	0.19	0.46	-0.05	0.52	0.06	0.39
9/6	0.09	0.14	0.46	0.47	0.52	0.71	-0.08	0.37
9/9	0.23	0.35	0.50	0.56	0.50	0.19	0.35	0.14
9/12	0.26	0.21	0.39	0.38	0.12	-0.16	0.36	0.30
9/18	0.15	0.23	0.14	0.18	0.15	-0.14	0.06	-0.37

Rank/hold combination	1995-2015 Individual	1995-2015 Individual *skip strategy*	1995-2015 Industry	1995-2015 Industry *skip strategy*	Global crisis period Individual	Global crisis period Industry	Internet Bubble Individual	Internet Bubble Industry
9/24	0.19	0.16	0.12	0.11	0.14	-0.15	-0.24	-0.22
12/3	-0.14	-0.02	0.40	0.25	-0.40	-0.33	-0.28	0.30
12/6	0.10	0.12	0.29	0.27	-0.16	0.04	0.28	0.05
12/9	0.33	0.31	0.41	0.28	-0.38	-0.02	0.74	0.38
12/12	0.21	-0.06	0.46	0.38	-0.15	-0.00	0.77	0.44
12/18	-0.04	-0.06	0.56	0.30	-0.65	0.80	-0.12	0.17
12/24	-0.02	-0.10	0.31	0.17	-0.48	0.55	-0.17	0.27
18/3	0.48	0.50	-0.00	0.46	-1.19	0.29	0.79	0.51
18/6	0.31	0.30	0.48	0.64	0.01	0.77	0.33	0.93
18/9	0.29	0.48	0.51	0.93	0.27	0.22	0.48	1.56
18/12	0.21	0.05	0.45	0.69	0.40	0.16	0.39	1.56
18/18	-0.22	-0.22	0.25	0.52	-0.49	3.37	-0.27	0.23
18/24	-0.24	-0.29	-0.04	0.15	0.03	1.39	0.96	-0.60

Appendix G-Consistency of firms on the FTSE 100 (year-to-year)

The table below represents the average percentage of firms that remain consistent components of the FTSE 100 from year-to-year.

Year-to-year	Percentage of consistent firms
1996	82%
1997	86%
1998	90%
1999	93%
2000	83%
2001	89%
2002	96%
2003	95%
2004	91%
2005	88%
2006	87%
2007	90%
2008	93%
2009	94%
2010	91%
2011	96%
2012	92%
2013	94%
2014	93%

Appendix H-Winner/Loser consistency (Firm-level)

	Instances of firm repetition in consecutive ranking periods		Instance of firm repetition in non-consecutive ranking periods	
	Winner portfolio	*Loser Portfolio*	*Winner portfolio*	*Loser Portfolio*
3 month ranking portfolios	84	74	104	81
6mth ranking portfolios	52	60	72	108
9mth ranking portfolios	32	29	55	50
12mth ranking portfolios	27	25	37	31
18mth ranking portfolios	10	15	26	20

Appendix I-Winner/Loser consistency (Industry level)

	Instances of industry repetition in consecutive periods		**Instances of *entire* portfolio repetition in consecutive periods**	
	Winner Portfolio	*Loser portfolio*	*Winner Portfolio*	*Loser portfolio*
3 month ranking portfolios	82	90	4	4
6mth ranking portfolios	47	50	2	2
9mth ranking portfolios	33	28	3	-
12mth ranking portfolios	22	22	1	-
18mth ranking portfolios	15	11	-	-

Appendix J- Industry appearances in winner and loser portfolios

		3mth ranking period	6mth ranking period	9mth ranking period	12mth ranking period	18mth ranking period
Finance, Insurance, Real Estate	**W**	27	9	8	4	4
	L	16	6	8	4	4
Services	**W**	26	12	8	6	4
	L	28	12	7	6	3
Manufacturing	**W**	13	18	4	3	4
	L	17	11	8	7	4
Wholesale Trade	**W**	26	12	9	4	4
	L	33	14	9	6	4
Agriculture, Forestry, Fishing	**W**	33	20	12	8	5
	L	39	16	11	9	6
Mining	**W**	31	26	12	10	6
	L	26	16	9	6	4
Retail Trade	**W**	31	13	8	7	3
	L	26	16	9	5	5