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

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

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Declaration

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

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Áine Murphy
March 2017
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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.
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<td>AMEX</td>
<td>American Stock Exchange</td>
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<tr>
<td>BF</td>
<td>Behavioural Finance</td>
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<td>BFI</td>
<td>Banking, Finance and Investments</td>
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<td>BHAR</td>
<td>Buy and Hold Return</td>
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<td>CAPM</td>
<td>Capital Asset Pricing Model</td>
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<td>CAR</td>
<td>Cumulative Abnormal Returns</td>
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<td>CRR</td>
<td>Cumulative Raw Returns</td>
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<td>EMH</td>
<td>Efficient Market Hypothesis</td>
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<td>FF3F</td>
<td>Fama and French (1993) Three Factor Model</td>
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<td>FTSE</td>
<td>Financial Times Stock Exchange</td>
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<td>IPO</td>
<td>Initial Public Offering</td>
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<td>IVol</td>
<td>Idiosyncratic volatility</td>
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<tr>
<td>LSN</td>
<td>Law of Small Numbers</td>
</tr>
<tr>
<td>LSPD</td>
<td>London Share Price Database</td>
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<tr>
<td>MAD</td>
<td>Market Abuse Directive</td>
</tr>
<tr>
<td>NASDAQ</td>
<td>National Association of Securities Dealers Automated Quotations</td>
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<tr>
<td>NYSE</td>
<td>New York Stock Exchange</td>
</tr>
<tr>
<td>PEAD</td>
<td>Post Earnings Announcement Drift</td>
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<tr>
<td>SIC</td>
<td>Standard Industry Classification</td>
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<tr>
<td>TAQ</td>
<td>Trade and Quote</td>
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<td>TTM</td>
<td>Technology, Telecommunications and Media</td>
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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 Tversky (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. 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. 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

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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.

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).


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.


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.


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

- Underreaction
- Positive feedback trading
- Conservatism bias
- Prospect theory
- Herding
- Anchoring, availability & representativeness
- Brokers/Analysts
- Rational explanations
- Firm-specific characteristics
- Stock market volatility
- Transaction costs
- Macroeconomic factors
- Liquidity risk
- Business cycles
- Momentum
- Disposition effect
- Momentum traders
- Herding
- Overconfidence
- Conflicts of interest

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
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 publicly 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**

Arbitrageurs hear of news and with the desire to gain from this information begin to trade. Their demand drives stock price up. The news is slowly diffused amongst investors initially leading to undereaction.

Arbitrageurs buy stocks leading to a stock price increase.

On viewing stock price increases, momentum traders buy stocks leading to investor 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.
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.


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.


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’.


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), Michaeley 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 univariate 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\(^4\) 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 \textit{et al.} (2007) highlight potential differences between the value of affiliated and unaffiliated analysts’ recommendations. Barber \textit{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 \textit{et al.} (2006) postulate that, perhaps in an attempt to avoid earnings disappointment, analysts of affiliated firms issue less optimistic recommendations and forecasts. Jacob \textit{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.

\(\text{See Appendix A for a full review of studies on international momentum.}\)

\(\text{Affiliated refers to an analyst who is employed by a firm that has investment activities and underwrites the securities of a firm.}\)
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 Team⁶ as a proxy for analyst reputation; those who appear on

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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. 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.

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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.


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 (Dzielski, 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’ 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.’

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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, 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

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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

⁹ 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. 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;

\[
R_{it} = \ln \left( \frac{P_t}{P_{t-1}} \right)
\]  

(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.
\[ R_{it} = \alpha_t + \beta_i(R_{mt}) + \varepsilon_{it} \]  \hspace{1cm} (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 \( t \);
\( \alpha_t \) is a constant factor that varies between securities;
\( \beta_i \) measure of systematic risk.

The error term (\( \varepsilon_{it} \)) 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;

\[ R_{it} = R_f + \beta_i(R_{mt} - R_f) + \varepsilon_{it} \]  \hspace{1cm} (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;
\( \beta_i \) measure of systematic risk;
\( \varepsilon_{it} \) 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 strategy12. Equation 4.4 below denotes FF3F;

\[ R_{it} - R_{ft} = \alpha_i + \beta_i (R_{mt} - R_{ft}) + s_i (SMB_t) + h_i (HML_t) + \epsilon_{it} \quad (4.4) \]

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.

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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)\textsuperscript{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\textsuperscript{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 $\text{ACAR}_W – \text{ACAR}_L > 0$. Where $\text{CAR}_{nt}$ for $n$ stocks at time $t$ is calculated by:

\textsuperscript{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/

\textsuperscript{14} Jegadeesh and Titman, (1993; 2001); Rouwenhorst, (1999); Moskowitz and Grinblatt, (1999) form equally weighted portfolios.
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\textsuperscript{15}. A month is skipped between rank and hold periods to avoid any bias associated with infrequent trading and bid-ask spread bias. Galariotios \textit{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.

\textbf{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

\[ CAR_{pt} = \frac{1}{N} \sum_{t=1}^{T} \sum_{i=1}^{n} \varepsilon_{it} \]  \hspace{1cm} (4.5)

\textsuperscript{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 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).

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

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.

### 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.

---

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 $\text{CAR}_t$ is denoted by $2S_t^2$;

\[
2S_t^2 = \frac{\sum_{n=1}^{N}(\text{CAR}_{wt} - \text{AR}_{wt})^2 + \sum_{n=1}^{N}(\text{CAR}_{Lt} - \text{AR}_{Lt})^2}{2(N-1)}
\]  \hspace{1cm} (4.6)

Where, $\text{CAR}_{wt}$ and $\text{CAR}_{Lt}$ are the cumulative average abnormal returns of winners and losers at time $t$ and $\text{AR}_{wt}$ and $\text{AR}_{Lt}$ 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;

\[
T_t = \left[ \text{ACAR}_{wt} - \text{ACAR}_{Lt} \right] / \sqrt{\frac{2S_t^2}{N}}
\]  \hspace{1cm} (4.7)
To test if $ACAR_w$ and $ACAR_L$ are statistically different from zero the standard deviation of the winner portfolio is calculated by;

$$S_t = \sqrt{\sum_{n=1}^{N}(AR_{wnt} - AR_{wt})^2 / N - 1}$$ \hspace{1cm} (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.

<table>
<thead>
<tr>
<th>Sector</th>
<th>N</th>
<th>Company per-year observations</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Panel A</td>
</tr>
<tr>
<td>Media</td>
<td>2</td>
<td>41</td>
</tr>
<tr>
<td>Technology</td>
<td>10</td>
<td>559</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Total= 600</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Panel B</td>
</tr>
<tr>
<td>Financials</td>
<td>33</td>
<td>3,108</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Total= 3,108</td>
</tr>
</tbody>
</table>

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.

<table>
<thead>
<tr>
<th>Panel A</th>
<th>Recommendations</th>
<th>Mean</th>
<th>Median</th>
</tr>
</thead>
<tbody>
<tr>
<td>All sectors</td>
<td></td>
<td>2.26</td>
<td>2</td>
</tr>
<tr>
<td>TTM sector only</td>
<td></td>
<td>2.17</td>
<td>2</td>
</tr>
<tr>
<td>All sectors</td>
<td></td>
<td>2.03</td>
<td>1</td>
</tr>
<tr>
<td>BFI sector only</td>
<td></td>
<td>2.21</td>
<td>2</td>
</tr>
<tr>
<td>Panel B</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All sectors</td>
<td></td>
<td>9.97</td>
<td>19.35</td>
</tr>
<tr>
<td>TTM sector only</td>
<td></td>
<td>20.95</td>
<td>15.13</td>
</tr>
<tr>
<td>All sectors</td>
<td></td>
<td>49.74</td>
<td>1.30</td>
</tr>
<tr>
<td>BFI sector only</td>
<td></td>
<td>41.26</td>
<td>22.83</td>
</tr>
</tbody>
</table>

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 Lakinsonshok (1979) observe forecast revisions impact on returns. Furthermore, Givoly and Lakinsonshok (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:

$$R_t = \alpha + \beta_1 \frac{M_F_{t-1}}{p_t} + \beta_2 \frac{MF_t}{p_t} + \beta_3 \frac{\Delta MF_t}{p_t} + \beta_4 \text{Rating}_t + \beta_5 \Delta \text{Rating}_t + \beta_6 \text{DUM}_t + \epsilon_t \quad (4.9)$$
Where\textsuperscript{21}:

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

$ME_{t,t-1}$ 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;

$\Delta MF_t$ 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.

$\varepsilon_t$ 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\textsuperscript{22}. Therefore, $ME_{t,t-1}$ 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

\textsuperscript{21} Use of term average refers to the average across sector, i.e. average earnings forecast are the average earnings forecast across sector.

\textsuperscript{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>
<thead>
<tr>
<th>Rating terms per recommendation category</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
</tr>
<tr>
<td>Strong Buy</td>
</tr>
<tr>
<td>Buy</td>
</tr>
<tr>
<td>Speculate</td>
</tr>
<tr>
<td>Standout/Outperform</td>
</tr>
<tr>
<td>Long-term Buy</td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>

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 portfolios⁴. Two-tailed t-statistics are reported in parentheses. T-statistics are estimated using the method of De Bondt and Thaler (1985).

<table>
<thead>
<tr>
<th>Hold period (Months)</th>
<th>Rank Period (months)</th>
<th>3</th>
<th>6</th>
<th>9</th>
<th>12</th>
<th>18</th>
<th>24</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>W</td>
<td>0.000</td>
<td>0.005</td>
<td>0.004</td>
<td>0.008</td>
<td>0.014</td>
<td>0.016</td>
</tr>
<tr>
<td></td>
<td>L</td>
<td>-0.000</td>
<td>-0.003</td>
<td>-0.008</td>
<td>-0.017</td>
<td>-0.015</td>
<td>-0.015</td>
</tr>
<tr>
<td>W-L</td>
<td>(0.05)</td>
<td>(2.13)</td>
<td>(2.41)</td>
<td>(4.12)</td>
<td>(3.68)</td>
<td>(3.39)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>6</td>
<td>-0.000</td>
<td>0.002</td>
<td>0.005</td>
<td>0.007</td>
<td>0.008</td>
<td>0.008</td>
</tr>
<tr>
<td></td>
<td>L</td>
<td>-0.002</td>
<td>-0.001</td>
<td>-0.005</td>
<td>-0.004</td>
<td>-0.003</td>
<td>-0.003</td>
</tr>
<tr>
<td>W-L</td>
<td>(1.03)</td>
<td>(2.11)</td>
<td>(4.56)</td>
<td>(3.73)</td>
<td>(3.06)</td>
<td>(1.82)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>9</td>
<td>-0.001</td>
<td>-0.001</td>
<td>0.001</td>
<td>0.004</td>
<td>0.003</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>L</td>
<td>-0.002</td>
<td>-0.002</td>
<td>-0.003</td>
<td>-0.007</td>
<td>-0.001</td>
<td>-0.002</td>
</tr>
<tr>
<td>W-L</td>
<td>(0.46)</td>
<td>(0.48)</td>
<td>(1.15)</td>
<td>(1.29)</td>
<td>(0.74)</td>
<td>(0.09)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>12</td>
<td>0.000</td>
<td>0.000</td>
<td>0.002</td>
<td>0.000</td>
<td>-0.000</td>
<td>-0.001</td>
</tr>
<tr>
<td></td>
<td>L</td>
<td>0.001</td>
<td>-0.001</td>
<td>-0.002</td>
<td>-0.003</td>
<td>-0.000</td>
<td>-0.000</td>
</tr>
<tr>
<td>W-L</td>
<td>(0.63)</td>
<td>(0.45)</td>
<td>(1.42)</td>
<td>(0.93)</td>
<td>(0.18)</td>
<td>(0.08)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>18</td>
<td>0.001</td>
<td>0.000</td>
<td>-0.000</td>
<td>-0.000</td>
<td>-0.004</td>
<td>-0.003</td>
</tr>
<tr>
<td></td>
<td>L</td>
<td>0.003</td>
<td>-0.003</td>
<td>-0.003</td>
<td>-0.002</td>
<td>-0.001</td>
<td>0.001</td>
</tr>
<tr>
<td>W-L</td>
<td>(1.72)</td>
<td>(1.12)</td>
<td>(1.04)</td>
<td>(0.69)</td>
<td>(0.77)</td>
<td>(0.84)</td>
<td></td>
</tr>
</tbody>
</table>

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

²⁴Results were not substantially altered with the use of value-weighted portfolios.
The performances of CARw – CARL 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).

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</table>

*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\textsubscript{w} – CAR\textsubscript{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.

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

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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.
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).

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*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).

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<td>(1.57)</td>
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<td>(0.16)</td>
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</table>

*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.

![Bar chart showing average monthly returns](image)

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. CARw-CARl 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).

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<th>Rank/Hold period (months)</th>
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<td>(0.28)</td>
<td>(1.08)</td>
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<td>(2.05)</td>
</tr>
<tr>
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<td>-0.008</td>
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<td>(0.93)</td>
<td>(0.36)</td>
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</tr>
<tr>
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</tr>
<tr>
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<td>(0.02)</td>
<td>(0.55)</td>
<td>(0.81)</td>
<td>(0.86)</td>
<td>(0.05)</td>
</tr>
</tbody>
</table>

*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. CARw-CARL 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).

<table>
<thead>
<tr>
<th>Rank/Hold period (months)</th>
<th>3</th>
<th>6</th>
<th>9</th>
<th>12</th>
<th>18</th>
<th>24</th>
</tr>
</thead>
<tbody>
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<td>0.017**</td>
<td>0.031*</td>
<td>0.046*</td>
<td>0.054*</td>
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<td>(5.06)</td>
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<td>0.021*</td>
<td>0.027*</td>
<td>0.021**</td>
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<td>0.008</td>
<td>0.002</td>
<td>-0.008</td>
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<td>(1.07)</td>
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<td>0.012***</td>
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</tr>
<tr>
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<td>(0.75)</td>
<td>(1.97)</td>
<td>(2.05)</td>
<td>(0.32)</td>
<td>(0.41)</td>
</tr>
<tr>
<td>18</td>
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<td>0.003</td>
<td>0.005</td>
<td>0.005</td>
<td>-0.006</td>
<td>0.007</td>
</tr>
<tr>
<td></td>
<td>(1.77)</td>
<td>(0.67)</td>
<td>(0.95)</td>
<td>(0.78)</td>
<td>(0.54)</td>
<td>(1.67)</td>
</tr>
</tbody>
</table>

*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. \( CAR_{i}^{+}-CAR_{i}^{-} \) 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).

<table>
<thead>
<tr>
<th>Rank/Hold period (months)</th>
<th>3</th>
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<th>9</th>
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<tr>
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<td>(0.04)</td>
<td>(0.01)</td>
<td>(1.79)</td>
<td>(1.25)</td>
</tr>
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<td>18</td>
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<td>0.006</td>
<td>0.002</td>
<td>0.002</td>
<td>0.009**</td>
<td>0.008***</td>
</tr>
<tr>
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<td>(0.06)</td>
<td>(1.55)</td>
<td>(0.45)</td>
<td>(0.32)</td>
<td>(5.83)</td>
<td>(2.41)</td>
</tr>
</tbody>
</table>

*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).

<table>
<thead>
<tr>
<th>Rank/Hold period (months)</th>
<th>3</th>
<th>6</th>
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<td>(0.64)</td>
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<td>(0.63)</td>
</tr>
<tr>
<td>18</td>
<td>0.002</td>
<td>0.005</td>
<td>0.005**</td>
<td>0.007**</td>
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<td>-0.004</td>
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<tr>
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<td>(1.87)</td>
<td>(3.12)</td>
<td>(3.13)</td>
<td>(0.47)</td>
<td>(1.04)</td>
</tr>
</tbody>
</table>

*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

3 month ranking period return

B

6 month ranking period return

114
Average monthly returns
Winner minus Loser

Holding Period

9 month ranking period return

Full Sample (1995-2015)
Global Financial Crisis (2005-2012)

12 month ranking period return

Full Sample (1995-2015)
Global Financial Crisis (2005-2012)
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 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.

![Graph showing ratio of buy-to-sell recommendations from 1995 to 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: 7.1:1. 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.

120
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.
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).

![Graph A](image1)

![Graph B](image2)

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).
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).
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.

<table>
<thead>
<tr>
<th>Event Month</th>
<th>Before the Internet/credit bubble burst</th>
<th>After the Internet/credit bubble burst</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Difference of CRRs</td>
<td>Difference of CARs</td>
</tr>
<tr>
<td></td>
<td>Mean</td>
<td>t-stat</td>
</tr>
<tr>
<td>Panel A: TTM Sector</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

-6 | 0.0028 (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 (4.74)* |
-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
After September 2007 negative CRRs are observed for all recommendation categories (Figure 5.23 C), with \textit{strong sell} outperforming other categories and remaining relatively consistent over the 13-month event window. The performance of the \textit{strong sell} category in comparison to the \textit{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 \textit{strong buy} to a \textit{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 present results pertaining to the TTM and BFI sectors respectively.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-0.136 (-0.64)</td>
<td>0.049 (1.02)</td>
</tr>
<tr>
<td>$\frac{ME_{t-1}}{P_t}$</td>
<td>-0.892 (-0.45)</td>
<td>0.002 (1.50)</td>
</tr>
<tr>
<td>$\frac{MF_t}{P_t}$</td>
<td>0.634 (0.07)</td>
<td>-0.000 (-1.06)</td>
</tr>
<tr>
<td>$\frac{\Delta MF_t}{P_t}$</td>
<td>0.015 (0.58)</td>
<td>0.000 (0.38)</td>
</tr>
<tr>
<td>Rating$_t$</td>
<td>0.034 (0.08)</td>
<td>-0.015 (-1.00)</td>
</tr>
<tr>
<td>$\Delta$Rating$_t$</td>
<td>-0.073 (-0.89)</td>
<td>0.008 (0.76)</td>
</tr>
<tr>
<td>DUM$_t$</td>
<td>-0.013 (-1.26)</td>
<td>-0.013 (-0.84)</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.047</td>
<td>0.096</td>
</tr>
</tbody>
</table>

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.
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).
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 subsample period, the slow levels of information diffusion leads to more underreaction 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

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


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Thomas, J. and Zhang, F. (2008) ‘Overreaction to intra-industry information transfers?’,

assignment experiment addressing the effects of moods on risk preferences’, [online]


biases’, *Science, 185*(4157), pp. 1124-1131.


Rochester.

Von Neumann, J. and Morgenstern, O. (1944) ‘*Theory of games and economic


## Appendix A—International evidence of momentum

<table>
<thead>
<tr>
<th>Author(s)</th>
<th>Strategy</th>
<th>Country/Index</th>
<th>Time period</th>
</tr>
</thead>
<tbody>
<tr>
<td>Antoniou et al. (2007)</td>
<td>Individual</td>
<td>France, Germany, United Kingdom</td>
<td>1977-2002</td>
</tr>
<tr>
<td>Bird and Whitaker (2003)</td>
<td>Individual</td>
<td>Germany, Italy, France, the Netherlands, Spain, Switzerland, United Kingdom.</td>
<td>1990-2002</td>
</tr>
<tr>
<td>Chan et al. (2000)</td>
<td>Individual</td>
<td>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.</td>
<td>1980-1995</td>
</tr>
<tr>
<td>Doukas and Mcknight (2005)</td>
<td>Individual</td>
<td>Austria, Belgium, Denmark, Finland, France, Germany, Italy, the Netherlands, Norway, Spain, Sweden, Switzerland, United Kingdom.</td>
<td>1988-2001</td>
</tr>
<tr>
<td>Galariotis et al. (2007)</td>
<td>Individual</td>
<td>United Kingdom.</td>
<td>1965-2005</td>
</tr>
<tr>
<td>Study</td>
<td>Research Type</td>
<td>Countries</td>
<td>Time Period</td>
</tr>
<tr>
<td>-------------------------------------------</td>
<td>---------------</td>
<td>---------------------------------------------------------------------------</td>
<td>---------------</td>
</tr>
<tr>
<td>Liu et al. (2011)</td>
<td>Individual</td>
<td>Australia, Austria, Belgium, Canada, Denmark, France, Germany, Hong Kong, Italy, Spain, the Netherlands, Norway, Russia, Singapore, South Korea, Spain, Sweden, Switzerland, Taiwan, United Kingdom.</td>
<td>1975-2006</td>
</tr>
<tr>
<td>McInish et al. (2008)</td>
<td>Individual</td>
<td>Japan, Hong Kong, Taiwan, Korea, Malaysia, Thailand, Singapore.</td>
<td>1999-2000</td>
</tr>
<tr>
<td>Naranjo and Porter (2007)</td>
<td>Individual</td>
<td>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.</td>
<td>1990-2004</td>
</tr>
<tr>
<td>Rouwenhorst (1998)</td>
<td>Individual</td>
<td>Austria, Denmark, France, Germany, Italy, the Netherlands, Norway, Spain, Sweden, Switzerland.</td>
<td>1980-1995</td>
</tr>
<tr>
<td>Study</td>
<td>Type</td>
<td>Countries</td>
<td>Period</td>
</tr>
<tr>
<td>------------------------------</td>
<td>------------</td>
<td>---------------------------------------------------------------------------</td>
<td>--------------</td>
</tr>
<tr>
<td>Rouwenhorst (1999)</td>
<td>Individual</td>
<td>Argentina, Brazil, Chile, Colombia, Greece, Indonesia, India, Jordan, Korea, Malaysia, Mexico, Nigeria, Pakistan, Nigeria, Portugal, Taiwan, Thailand, Turkey, Venezuela, Zimbabwe.</td>
<td>1975-1997</td>
</tr>
<tr>
<td>van der Hart <em>et al.</em> (2003)</td>
<td>Individual</td>
<td>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.</td>
<td>1985-1999</td>
</tr>
<tr>
<td>van Dijk and Huibers (2002)</td>
<td>Individual</td>
<td>Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom.</td>
<td>1987-1999</td>
</tr>
</tbody>
</table>
## Appendix B-Momentum returns global financial crisis period (Individual)

<table>
<thead>
<tr>
<th>Rank Period (months)</th>
<th>3</th>
<th>6</th>
<th>9</th>
<th>12</th>
<th>18</th>
<th>24</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>W</strong></td>
<td>0.003</td>
<td>0.009</td>
<td>0.015</td>
<td>0.021</td>
<td>0.032</td>
<td>0.056</td>
</tr>
<tr>
<td><strong>L</strong></td>
<td>0.008</td>
<td>0.009</td>
<td>0.017</td>
<td>0.011</td>
<td>0.024</td>
<td>0.026</td>
</tr>
<tr>
<td><strong>W-L</strong></td>
<td>-0.005</td>
<td>0.000</td>
<td>-0.002</td>
<td>0.010</td>
<td>0.007</td>
<td>0.032***</td>
</tr>
<tr>
<td>(0.87)</td>
<td>(0.00)</td>
<td>(0.28)</td>
<td>(1.08)</td>
<td>(0.61)</td>
<td>(2.05)</td>
<td></td>
</tr>
<tr>
<td><strong>W</strong></td>
<td>0.001</td>
<td>-0.000</td>
<td>0.008</td>
<td>0.009</td>
<td>0.018</td>
<td>0.025</td>
</tr>
<tr>
<td><strong>L</strong></td>
<td>0.011</td>
<td>0.007</td>
<td>0.019</td>
<td>0.016</td>
<td>0.021</td>
<td>0.020</td>
</tr>
<tr>
<td><strong>W-L</strong></td>
<td>-0.010***</td>
<td>-0.008</td>
<td>-0.012***</td>
<td>-0.008</td>
<td>-0.003</td>
<td>0.005</td>
</tr>
<tr>
<td>(2.09)</td>
<td>(1.20)</td>
<td>(1.93)</td>
<td>(0.99)</td>
<td>(0.36)</td>
<td>(0.39)</td>
<td></td>
</tr>
<tr>
<td><strong>W</strong></td>
<td>-0.000</td>
<td>0.006</td>
<td>0.003</td>
<td>0.016</td>
<td>0.010</td>
<td>0.020</td>
</tr>
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<td><strong>L</strong></td>
<td>-0.000</td>
<td>0.001</td>
<td>0.002</td>
<td>0.003</td>
<td>0.007</td>
<td>0.016</td>
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<tr>
<td><strong>W-L</strong></td>
<td>0.000</td>
<td>0.005</td>
<td>0.005</td>
<td>0.002</td>
<td>0.003</td>
<td>0.004</td>
</tr>
<tr>
<td>(0.15)</td>
<td>(1.49)</td>
<td>(1.42)</td>
<td>(0.36)</td>
<td>(0.42)</td>
<td>(0.35)</td>
<td></td>
</tr>
<tr>
<td><strong>W</strong></td>
<td>0.005</td>
<td>0.004</td>
<td>0.003</td>
<td>0.002</td>
<td>0.005</td>
<td>0.003</td>
</tr>
<tr>
<td><strong>L</strong></td>
<td>0.007</td>
<td>0.006</td>
<td>0.003</td>
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*significant at 1% level
** significant at 5% level
***significant at 10% level
### Appendix C-Momentum returns Internet bubble period (Individual)

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*significant at 1% level  
**significant at 5% level  
***significant at 10% level
## Appendix D: Momentum returns global financial crisis period (Industry)

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*significant at 1% level
**significant at 5% level
***significant at 10% level
Appendix E - Momentum returns Internet bubble period (Industry)

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*significant at 1% level
**significant at 5% level
***significant at 10% level
## Appendix F-Sharpe Ratios

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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.

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<thead>
<tr>
<th>Year-to-year</th>
<th>Percentage of consistent firms</th>
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<tr>
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<td>91%</td>
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<tr>
<td>2005</td>
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<td>2010</td>
<td>91%</td>
</tr>
<tr>
<td>2011</td>
<td>96%</td>
</tr>
<tr>
<td>2012</td>
<td>92%</td>
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<tr>
<td>2013</td>
<td>94%</td>
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<td>2014</td>
<td>93%</td>
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Appendix H-Winner/Loser consistency (Firm-level)

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<th>Instances of firm repetition in consecutive ranking periods</th>
<th>Instance of firm repetition in non-consecutive ranking periods</th>
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<tbody>
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<td>27</td>
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Appendix I-Winner/Loser consistency (Industry level)

<table>
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<th>Instances of industry repetition in consecutive periods</th>
<th>Instances of entire portfolio repetition in consecutive periods</th>
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## Appendix J- Industry appearances in winner and loser portfolios

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<th>9mth ranking period</th>
<th>12mth ranking period</th>
<th>18mth ranking period</th>
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<tbody>
<tr>
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<td>L 16</td>
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<td></td>
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