An investigation into the winner-loser and momentum anomalies in four medium-sized European markets

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A Dissertation Submitted for the Degree of Doctor of Philosophy
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January 2013

DECLARATION

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ACKNOWLEDGEMENTS

I wish to thank Professor Liam Gallagher for his guidance, encouragement, and expertise throughout the process of completing this dissertation.

I am appreciative of the support of my colleagues at Waterford Institute of Technology.

I am grateful to my parents and family for all of their love and encouragement.

Finally, I wish to express my gratitude to my wife Sinéad for her unwavering love, support, patience, and selflessness throughout the preparation of this thesis.

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ABSTRACT

An investigation into the winner-loser and momentum anomalies in four medium-sized European markets

Cormac O' Keeffe

The allocative efficiency of financial markets is of central importance to academics, investors, and regulators. However, there is a dearth of research relating to the efficiency of medium-sized European markets. This thesis addresses this research gap by examining the winner-loser and momentum anomalies in Ireland, Greece, Norway, and Denmark. The profitability of contrarian and strength rule strategies is examined using a variety of models and rank and holding periods of differing lengths. Existing research establishes a strong link between the two anomalies under review and the behaviour of brokers. Therefore, this study also analyses the economic value and impact of brokers' recommendations and forecasts in the Irish market.

There is substantial evidence of market inefficiency with significant return continuation in Ireland and reversals in the other three markets. Risk-adjusted returns are significantly higher when portfolios are comprised of extreme winners and losers. There is evidence of momentum followed by reversal in two of the four markets. Average monthly momentum returns peak after approximately two months in Ireland, while the optimum approach in the other three markets involves skipping one year before implementing the contrarian strategy.

Brokers' recommendations earn modest abnormal returns by exploiting the superior performance of small firms with positive momentum. However, such returns are significantly reduced by the relatively poor performance of stocks with low book-to-market and high earnings-to-price ratios that brokers favourably recommend. Recommendation revisions are of greater value but fail to outperform relatively straightforward trading strategies based on momentum, size, book-to-market, and price-earnings ratios. Brokers' recommendations do not induce a significant increase in trading activity. Taken together, this suggests that brokers follow momentum strategies but are not a key driver of momentum.

LIST OF ABBREVIATIONS AND ACRONYMS

ARCH:	Autoregressive Conditional Heteroscedasticity
BHAR:	Buy-and-Hold Abnormal Returns
B/M:	Book-to-Market ratio
CAPM:	Capital Asset Pricing Model
CAR:	Cumulative Abnormal Returns
CFO:	Chief Financial Officer
CRSP:	Center for Research and Stock Prices
DISP:	Dispersion
E/P:	Earnings-to-Price ratio
EMH:	Efficient Market Hypothesis
EPS:	Earnings Per Share
GARCH:	Generalised Autoregressive Conditional Heteroscedasticity
IPO:	Initial Public Offering
ln:	Natural logarithm
MM:	Market Model
NASD:	National Association of Securities Dealers (NASD)
OLS:	Ordinary Least Squares
P/E:	Price/Earnings ratio
PEAD:	Post-Earnings Announcement Drift
VOL:	Volume
Reg FD:	Regulation Fair Disclosure
SV:	Standardised Volume

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Chapter One

Introduction

1.1 Introduction

This thesis examines the winner-loser and momentum anomalies in four medium-sized European markets (Ireland, Greece, Norway, and Denmark) and also analyses the economic value and impact of brokers' recommendations and forecasts in the Irish market. The study represents a test of the efficiency of four medium-sized European markets with an emphasis on the role of behavioural factors and brokers in explaining the two anomalies. This chapter outlines the background and rationale to the research and provides an overview of the research objectives and design and the structure of the remaining chapters.

1.2 Background to the study

Valuing shares is a complex decision-making process. Standard finance theory asserts that 'economic man' correctly assesses the probability of each outcome and reaches a rational valuation. The expected utility theorem (von Neumann and Morgenstern 1947 cited in Tversky and Kahneman 1984, p.343) posits that the 'representative agent' acts rationally by choosing between risky outcomes on the basis of expected utility alone. Furthermore, the theory states that agents adhere to the axioms of choice (transitivity, completeness, convexity/continuity, and independence), are assumed to be risk averse (Bernoulli 1738 cited in Tversky and Kahneman 1984, p.341), and update their beliefs according to Bayes' rule. An implicit assumption of this traditional theory is that cognitive biases and investor sentiment cannot affect asset prices. The actions of any irrational agents are either self-cancelling or offset by the process of arbitrage, thereby preventing them from impacting share prices.

However, in reality people are often risk seekers and make decisions predicated on heuristics and mental frames that are often capricious and inflexible (Kahneman and Tversky, 1979).

Furthermore, people regularly buy both insurance policies and lottery tickets (Friedman and Savage, 1948), overreact and underreact in violation of Bayes' rule and exhibit a vast array of other cognitive biases. A number of observed paradoxes (for example, Allais, St Petersburg, and Ellsberg) have cast a further shadow over the validity of expected utility theory. Observed levels of trading volume are incongruous with standard theory; as such excessive volume requires heterogeneous beliefs. Furthermore, the trades of irrational individuals will not be self-cancelling in the presence of herding behaviour and noise traders may impact prices due to limits to arbitrage.

A major tenet of standard finance theory is the Efficient Market Hypothesis (EMH). A financial market is said to be informationally efficient if current prices fully reflect all available information. Fama (1970) identified three levels of market efficiency: weak; semi-strong; and strong, each differing with respect to the relevant definition of 'information'[1]. The concept of a random walk is central to the EMH. Bachelier (1900 cited in Dimson and Mussavian 1998, p.92) incorporated the concept of Brownian motion in finance theory, stating that "past, present and even discounted future events are reflected in market price, but often show no apparent relation to price changes". Fama (1965, p.34) states that the random walk implies that "successive price changes are independent, identically distributed random variables".

One of the challenges that any study of market efficiency faces is the appropriate definition of 'efficiency'. The definition has gradually evolved over time and critics of the EMH suggest that these constant refinements constitute a moving of the goalposts in response to mounting evidence of anomalies.

Originally, Fama (1965) defined an 'efficient' market as one:

> where there are large numbers of rational, profit-maximisers actively competing, with each trying to predict future market values of individual securities, and where important current information is almost freely available to all participants (p.76).

[1] Past price, publicly available information, and all information, respectively.

In such a market "stock prices follow random walks and at every point in time actual prices represent good estimates of intrinsic values" and prices will over-adjust as often as they will under-adjust (Fama, 1965, p.40).

Shiller (1984, p.459) states that the argument that share prices represent good estimates of intrinsic values at every point in time "represents one of the most remarkable errors in the history of economic thought". The quixotic view of the market that Shiller (1984) attacks has been supplanted by the less stringent requirement that an efficient market does not permit investors to *consistently* and *predictably* make economic profits after accounting for transaction costs and risk. Fama (1991) acknowledges that information and trading costs are clearly positive and thus rejects the strong version of the EMH, which suggests that such costs should be zero. Fama (1991, p.1575) presents a "weaker and economically more sensible version of the efficiency hypothesis", where security prices "reflect information to the point where the marginal benefits of acting on information do not exceed the marginal costs". It is this definition that this study uses in order to test market efficiency.

The EMH implies that brokers do not have an informational advantage and that their recommendations do not generate abnormal returns on average. However, Grossman and Stiglitz (1980) assert that perfect market efficiency is impossible as the concept represents an immutable paradox. If information is costly to gather and prices always fully reflect information then investors have no incentive to spend time and money collecting information and trading on it. In this case markets cannot be informationally efficient as information is not impounded into prices. There must be a marginal reward to incentivise research and trade and prices must only partly reflect private information.

The empirical validity of the EMH has been called into question by a series of anomalies. An anomaly refers to evidence that is incongruous with the predictions of standard finance theory. Such anomalous evidence violates at least one of the principles of market efficiency, the random walk hypothesis, or investor rationality as defined by the axioms of choice. The financial literature is replete with such anomalous evidence. For example, the existence of bubbles is at odds with the idea of efficient markets as standard theory postulates that informed rational investors arbitrage prices back to their correct level. Furthermore, equity returns are excessively high and volatile[2] and a catalogue of anomalies suggests that returns are predictable.

Such anomalies are broadly categorised as calendar (seasonal) or fundamental. Calendar anomalies refer to the existence of systematic abnormal returns at certain calendar times; whereas fundamental anomalies refer to systematic divergences between the expected and actual returns of stocks with certain firm-specific characteristics. The key calendar anomalies include the January, day-of-the-week, Halloween, turn-of-the-month, and holiday effects[3]; the principal fundamental anomalies are the size, price-earnings, winner-loser and momentum effects.[4] There is also a considerable body of evidence linking stock returns to mood-related variables such as the weather, lunar cycles, sports results, biorhythms, Seasonal Affective Disorder, and superstitions[5].

Many of the above anomalies disappeared when subjected to out-of-sample testing or alternative econometric specifications. The anomalous returns may have been time- or model-specific, or the process of arbitrage may have caused abnormal returns to subside after the anomaly was publicised. However, two interrelated fundamental anomalies have largely defied explanation and remain two of the most pervasive and enduring puzzles in financial economics.

The momentum and winner-loser anomalies refer to the observation that abnormal returns are positively and negatively serially correlated, respectively. It is these two anomalies that are the principal focus of this thesis. There is strong evidence in support of both strategies in the form of return continuation followed by reversal due to the different holding periods typically associated with each anomaly.

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[2] See Mehra and Prescott (1985) and Shiller (1981), respectively.
[3] See for example, Rozeff and Kinney (1976); Cross (1973); Bouman and Jacobsen (2002); Ariel (1987); and Fields, (1934), respectively.
[4] See for example, Banz (1981); Basu (1977); De Bondt and Thaler (1985); and Jegadeesh and Titman (1993), respectively.
[5] See for example, Hirshleifer and Shumway (2003); Yuan *et al.* (2006); Edmans *et al.* (2007); and Dowling and Lucey (2005).

The winner-loser (overreaction) effect refers to the tendency for stocks that have performed poorly (well) over a specified period to perform well (poorly) in the subsequent period. The effect implies a reversal of fortunes that manifests itself in negative serial correlation in abnormal returns. A contrarian investment strategy attempts to exploit return reversals by buying past losers and contemporaneously short-selling past winners. The winner-loser anomaly is inextricably linked to the influential work of De Bondt and Thaler (1985). However, research on overreaction and value investing dates back at least to Keynes (1936) and Graham (1949 cited in De Bondt and Thaler, 1985), respectively.

Power and Lonie (1993, p.326) state that "the overreaction effect has a claim to be regarded as one of the most important anomalies investigated during the 1980s". The authors posit three reasons why the anomaly merits extensive examination. First, contrarian investment strategies are associated with significantly larger returns and lower transaction costs than other anomalies. Second, the anomaly is more intuitively appealing than other stock market puzzles; and finally, the anomaly is built on a solid foundation of evidence from cognitive psychology documenting individuals' tendency to overreact.

The momentum (underreaction) effect is the opposite of the overreaction effect and manifests itself in return continuation (positive serial correlation). Strength rule strategies attempt to profit from momentum by longing past winners and shorting past losers in the anticipation of a continuation of past performance. The concept of return momentum is synonymous with Jegadeesh and Titman (1993). However, research into positive serial correlation in returns can be traced back to the seminal work of Cowles and Jones (1937), Levy (1967), and Ball and Brown (1968).

Fama (1998, p.304) concedes that the post-earnings-announcement drift is an anomaly that is "above suspicion" and labels short-term continuation as an "open puzzle". Such is the broad consensus regarding the existence of return continuation that a momentum factor is commonly included in return-generating models, most notably in Carhart's (1997) four-factor model.

The above violations of standard theory and a burgeoning catalogue of anomalies that contradict the EMH led to the development of prospect theory (Kahneman and Tversky, 1979) and the incorporation of cognitive biases and heuristics into an alternative paradigm known as Behavioural Finance (BF).

Barber and Odean (1999) state that:

> Behavioral finance relaxes the traditional assumptions of financial economics by incorporating … observable, systematic, and very human departures from rationality into standard models of financial markets (p.41).

BF replaces the quixotic view of the market as described by standard theory with the notion that agents often use time-saving heuristics, are influenced by psychological factors such as affect, regret, greed, fear, and overconfidence and make systematic errors that render share prices predictable. Two of the most important cognitive biases are over- and underreaction and these are the key focus of this study. Brokers are not immune to making such errors and their behaviour may lead to investors acting in a more co-ordinated fashion, thereby amplifying any biases and in turn affecting share prices in a material and predictable manner.

For at least two decades criticism of EMH was viewed as heretical and the ideas of BF were accordingly received with scepticism and controversy. However, BF has garnered favour over the last three decades and the school of thought is accepted as the dominant paradigm in many quarters. Indeed, the alternative to BF, where psychology and sentiment have no part to play in financial decision making and all prices are set by rational agents, is difficult to countenance. As Statman (1999, p.26) states "people are 'rational' in standard finance; they are 'normal' in behavioral finance". Thaler (1999, p.16) proclaims the "end of behavioural finance" as he asks "what other sort of finance is there?"

Although Thaler's proclamation may have proven somewhat premature, the growing catalogue of anomalies means that a set of theories that incorporate investor irrationality is becoming the accepted paradigm, rather than 'anomalous'. The term 'anomaly' is itself a loaded term, suggesting that any evidence consistent with a violation of the EMH is merely an ‘exception that proves the rule’. Instead of being viewed as anomalous to the EMH, behaviouralists may prefer to refer to such evidence as confirmatory, as it is consistent with BF models. This thesis will examine the role of behavioural factors, such as underreaction, overreaction, and herding, in explaining the two anomalies under review and the impact of the behaviour of brokers.

Brokers and analysts perform an important intermediary role in financial markets; issuing advice, facilitating trades, and transferring information from companies to investors. Starting with Cowles (1933), there has been extensive research on the economic value and impact of brokers’ recommendations; however, a consensus on these issues remains elusive. There is abundant evidence to suggest that brokers play a pivotal role in explaining the momentum and reversal anomalies[6].

1.3 Rationale

This study is motivated by a desire to gain a greater understanding of the functioning of financial markets by examining two of the most important anomalies in financial economics and analysing the role of a key financial participant – brokers. The research is driven by a strong personal interest in the topics under review and perceived gaps in the existing literature.

The allocative and informational efficiency of financial markets are of central importance to practitioners, investors, corporations, and regulators. Financial theory is fundamentally based on the assumption that financial agents and markets are rational. Evidence to the contrary may indicate the need for alterations to existing models, or in extreme cases, the need for a new paradigm that more accurately reflects the observed patterns of behaviour.

Practitioners rely heavily on contrarian and value investment strategies that are a key focus of this study. The considerable success of Benjamin Graham, George Soros, and Warren Buffett possibly represents the most immutable contradiction of standard theory’s assertion

[6] See for example Moshirian *et al.* (2009); Jegadeesh *et al*. (2004); Aitken *et al.* (2000); and Womack (1996).

that returns are unpredictable. Furthermore, the overreaction phenomenon has implications beyond financial economics. Dreman and Lufkin (2000, p.61) state that overreaction "can be the major cause of financial bubbles and panics".

Brokers and analysts play an important intermediary role in financial markets; facilitating trade and providing investment advice. The earnings forecasts of analysts are a key input into equity valuation models and their behaviour can have a significant impact on the allocation of scarce financial resources. Bernard (1990 cited in Olsen, 1996) shows that earnings forecasts affect stock prices and returns, while De Bondt and Thaler (1990) assert that brokers are key contributors to market overreaction.

Schipper (1991) outlines the motivations for the predominant use of analysts' forecasts as a proxy for market expectations. On average, analysts' forecasts of earnings are more accurate and forecast errors elicit a greater trading response than those of statistical models based on realised earnings. Brown and Caylor (2005) outline the increased importance of security analysts in financial markets. The authors document a significant increase in the number of analysts, the number of covered firms, media attention paid to analysts' forecasts, and the accuracy of such forecasts.

Proponents of the standard theory argue that the presence of a small number of irrational investors does not necessarily pose a significant challenge to the EMH. However, market efficiency is unlikely to persist if analysts are prone to irrationalities. The output of brokers may contribute to the interrelated phenomena of return continuation and reversal. Brokers may have the effect of co-ordinating the actions of individual investors, thereby leading to herding and overreaction. This is particularly germane if brokers follow momentum strategies. If a sufficient number of investors follow the recommendations of such brokers then this advice may constitute a self-fulfilling prophecy, leading to return continuation.

These factors are accentuated by analysts' observed reluctance to revise forecasts and recommendations and by the finding that they are prone to cognitive biases that contribute to momentum returns such as overconfidence, biased self-attribution, and underreaction. If these factors cause prices to overshoot their fundamental value a subsequent reversal may ensue. Therefore, it is worth devoting considerable attention to the role of analysts and their impact on the functioning of financial markets and their role in explaining documented anomalies.

1.4 Research objectives

This study aims to fill a number of perceived gaps in the literature. The overarching goal is to examine the profitability of contrarian and momentum investment strategies on a number of medium-sized European bourses. Any significant profits arising from either strategy would seem to violate the EMH. The thesis aims to explore the theories postulated to explain the two anomalies, with particular emphasis on behavioural causes and the role of brokers. In essence, the principal goal is to take a significant step towards answering the call to action of Michaely *et al*. (1995, p.606), who state that "we hope future research will help us understand why the market appears to overreact in some circumstances and underreact in others".

The overarching objectives vis-à-vis brokers are to ascertain whether they follow momentum strategies, are prone to cognitive biases and conflicts of interest, and whether their output has predictive power and induces trading activity. Affirmative answers to these questions would imply a strong link between the behaviour of brokers and the momentum and reversal anomalies.

A number of specific research questions will be addressed in this study. These include:

1. Is it possible to make economically and statistically significant risk-adjusted returns by following strength rule and contrarian strategies in the four markets under review?
2. Is it possible to ameliorate returns by employing alternative rank and holding periods and hybrid strategies?
3. Are any abnormal returns due to rational or behavioural factors?
4. Do Irish brokers appear to be more prone to conflicts of interest than their international counterparts?
5. To what extent do brokers follow momentum and contrarian strategies?

6. Do brokers’ recommendations have predictive power and what are the volume and price impacts of their output?

1.4.1 Contribution

This study makes a number of important contributions to the body of research relating to the momentum and reversal anomalies and the value and impact of brokers’ recommendations. Above all, it fills an important research gap and minimses data-snooping bias by using relatively under-utilised markets. Existing research is predominantly centred on large developed markets such as the US and UK and the emerging and recently liberalised markets of Asia. There is a dearth of research on small- to medium-sized European markets, which this study aims to address by focussing on Ireland, Greece, Norway, and Denmark. The market structure in these countries differs from those of the more developed markets that are often the focus of existing studies. The possible links between positive feedback trading and bubbles merits a closer examination of share price dynamics in two markets that experienced dramatic crashes (Greece and Ireland).

The study is of interest to investors and academics alike and aims to give a better understanding of the return-generating process and volatility of price movements in equities and provides further evidence on the efficiency of the four markets under review. An understanding of whether share prices on these stock exchanges overreact or underreact will provide valuable insights into the information content of earnings announcements and the effect of news. While previous studies have examined the two trading strategies separately, few have attempted to combine them in recognition of their shared causes and differing holding periods.

A number of models are employed, with varying degrees of sophistication in terms of their treatment of risk, in order to assess whether any excess abnormal returns are merely a rational reward for extra risk or whether they point towards market inefficiency. The inclusion of a number of hybrid strategies provides a broader perspective on the potential trading profits that can be generated by exploiting continuation followed by reversal.

The economic value of brokers' output and their susceptibility towards conflicts of interest are of great interest to investors and regulators alike. Considerable funds are expended on the research conducted by financial analysts. It is important to ascertain whether such an investment is a worthwhile undertaking or whether it constitutes an economic loss to investors. This study also makes an important contribution by focussing on the relationship between brokers' output and the two anomalies.

The oligopolistic nature of the Irish brokerage industry and the traditional ties between Irish brokerage firms and banks merit close examination as they may accentuate conflicts of interest and herding. This is of interest to regulators as efforts to tackle conflicts of interest in Europe have lagged behind those in the US.

This study also implements a number of novel methodological approaches. First, cross-product ratios and rank correlation coefficients are frequently employed to evaluate the persistence of fund managers' performance. However, to the best of the author's knowledge they have never been used to analyse return dynamics in relation to the momentum and reversal anomalies. Second, excluding overlapping observations mitigates potential cross-sectional dependence issues and provides a clearer picture of the price impact of brokers' recommendations. Third, including a small-firm asset helps to minimise microstructure bias without reducing the number of stocks analysed. Fourth, the use of rank and holding periods of varying lengths for both strategies offers valuable insights into the dynamics of returns. Finally, this study measures analysts' opinions on the prospects of firms using expected price change as a percentage of current price, in addition to the traditional recommendation levels. The former is a continuous variable, which provides a greater scope for differentiating between the strength of each observation. Furthermore, a comparison of the two variables sheds light on potential inconsistencies in brokers' output.

1.5 Research design

This thesis employs a quantitative approach to answer the research questions outlined in section 1.4. It should be noted that tests of market efficiency run into the joint-hypothesis problem in that any abnormal excess return found may not be an indication of market inefficiency but instead may be indicative of inefficiencies in the models used. Fama (1991, p.1576) stresses that "… when we find anomalous evidence on the behavior of returns, the way it should be split between market inefficiency or a bad model of market equilibrium is ambiguous". Similarly, Statman (1999, p.21) argues that "the problem of jointly testing market efficiency and asset-pricing models dooms us to futile attempts to determine two variables with only one equation". In light of this, a suite of models is employed in order to increase the robustness of all findings and conclusions.

The momentum and reversal anomalies are tested on each of the four markets by measuring the profitability of the contrarian and strength rule strategies using three models; the adjusted market model; market model; and the Capital Asset Pricing Model (CAPM).

The value, veracity, and impact of brokers' output are tested on the Irish market by analysing panel data relating to three forms of projections; Earnings Per Share (EPS) forecasts; target prices; and overall recommendation category. A combination of event- and calendar-based strategies is employed in conjunction with a number of models and holding periods.

The data relating to brokers is analysed along three temporal dimensions. First, brokers' recommendations are compared to historic variables, such as momentum, trading volume, size, and earnings-to-price ratios, in order to ascertain the characteristics of stocks that brokers favour and to assess whether they follow momentum or contrarian strategies. Second, the contemporaneous price targets and recommendations of each broker are analysed in order to determine whether the output of brokers paints a consistent picture of their opinions of the prospects of each firm. Third, the value and impact of brokers' output is scrutinised by examining the relationship between recommendations and future returns and trading volume.

1.6 Structure of the thesis

The remainder of this thesis is organised as follows. **Chapters two and three** provide the theoretical framework underpinning this research by synthesising the literature on the momentum and reversal anomalies respectively. A discussion of the abundant evidence across geographic and temporal dimensions is presented and a distinction is drawn between rational and behavioural explanations for the putative anomalies. The evidence in favour of the anomalies is pervasive and persistent and attempts to reconcile the evidence with rational explanations have proven to be largely futile.

Chapter four discusses the literature on the relationship between the behaviour of brokers and the two anomalies under review. Three key broad themes emerge. First, brokers are prone to conflicts of interest, causing them to issue overly optimistic forecasts and recommendations. They also herd and recommend stocks that have existing momentum. Second, investors tend to take brokers' advice at face value and such recommendations and forecasts thus impact share prices. Third, brokers' advice is often of insignificant economic value to investors but they trade on it nonetheless, thereby pushing share prices beyond their fundamental values, leading to a subsequent reversal. Taken together, this strongly suggests that brokers play a central role in the dynamics of the momentum and reversal anomalies.

Chapter five discusses the data and methodology pertaining to this thesis, outlining the data collection process and the models employed to address the research objectives detailed in section 1.4.

Chapter six presents the findings relating to the momentum and reversal anomalies. There is substantial evidence of market inefficiency with significant return continuation in Ireland and reversals in the other three markets. Risk-adjusted returns are significantly higher when portfolios are comprised of extreme winners and losers. There is evidence of momentum followed by reversal in two of the four markets and in general the optimum contrarian strategy involves skipping the first post-ranking year before implementing the contrarian investment strategy for one year. The optimum momentum strategy in Ireland involves ranking stocks over a nine-month period and holding them for a period of approximately two months.

Chapter seven analyses the value, veracity, and impact of brokers' output. The most notable conclusion is the consistent and robust tendency for brokers to tilt their recommendations towards firms with positive momentum. The long-term relationship between brokers' recommendations and abnormal returns and volume strongly suggests that brokers are principally followers, rather than leaders, in terms of momentum. Investors could generate greater abnormal returns by simply focusing on small firms with high momentum and book-to-market (B/M) ratios, rather than by following analysts' advice. Irish brokers are considerably more optimistic than their international counterparts and their recommendations generate larger abnormal returns. This superior performance is attributable to the performance of upgrades, which exploit momentum in returns. Finally, there is a marked lack of consistency between the recommendations and price forecasts of brokers.

Chapter eight concludes the thesis by synthesising the key findings and discussing their implications. It also outlines the contributions and limitations of the study and provides recommendations for further research.

Chapter Two

Momentum

2.1 Introduction

This chapter synthesises the literature pertaining to the momentum anomaly. It commences with the background to the momentum effect, followed by a discussion of the causes that have been postulated to elucidate its existence and persistence. The hypothesised causes are split into two broad schools of thought. Section 2.4 summarises the explanations for the apparent anomaly that are consistent with market efficiency. Behavioural theories are outlined in section 2.6, while the breakdown of momentum returns along a number of dimensions is analysed in section 2.7. Section 2.8 introduces the important role of brokers in explaining the anomaly, while conclusions are drawn in section 2.9.

2.2 The momentum anomaly

The momentum effect is possibly the most puzzling and persistent anomaly financial economics. There is a broad consensus on the existence of a momentum (or post-earnings-announcement drift) effect. It provides the most stern and stubborn test to the efficiency and rationality of financial markets. Fama (1998, p.304) concedes that the post-earnings-announcement drift is an anomaly that is "above suspicion" and labels short-term continuation as an "open puzzle". There is considerably less agreement on what the causes of such an anomaly, or indeed whether it is an anomaly at all. This chapter outlines the empirical evidence pertaining to the momentum effect and discusses the theories postulated to explain its persistence.

Levy (1967, p.609) concludes that "superior profits can be achieved by investing in securities which have historically been relatively strong in price movement". Jegadeesh and Titman (1993) find that a strength rule strategy, which involves buying stocks that have performed well in the past three to twelve months ('winners') and short selling those that have underperformed in the same period ('losers'), generates significant risk-adjusted returns in the US.

Jegadeesh and Titman (1993) examine 16 strategies based on rank and holding periods of three, six, nine, and 12 months. The authors analyse a further 16 strategies where a week is skipped between the rank and holding period in order to minimise microstructure biases. The optimum strategy ranks stocks on the basis of their performance over the past 12 months and holds winners and short sells losers for three months. This strategy generates 1.31% per month, rising to 1.49% when a week is skipped. Return continuation is only present for past winners, as past losers register positive abnormal returns for all 32 strategies. Continuation in returns over the first year is followed by a partial reversal in the subsequent two years.

The profitability of a strength rule has been confirmed in international markets and for out-of-sample time periods. Jegadeesh and Titman (2001) update their earlier study and find that momentum returns persist. Further evidence of momentum in US stocks is provided by, *inter alios,* Lee and Swaminathan (2000), Grundy and Martin (2001), Lewellen (2002), and Ji (2012), in addition to a host of studies that examine the US in conjunctions with other markets. Notably, Gutierrez and Kelley (2008) find evidence of momentum in the short run, as well as the traditional holding period of 6-12 months deployed by the majority of studies.

Long before the seminal paper by Jegadeesh and Titman (1993) or the work of Levy (1967), Cowles and Jones (1937) examined the return continuation when estimating *a posteriori* probabilities in stock prices. By measuring the frequency of reversals and sequences (consecutive movements of opposite and same signs respectively), Cowles and Jones (1937) measure the probability of the market increasing over a period of one hour, day, week, month or year, following an increase over the previous period of equal length.

A probability of one-half would be consistent with a random walk, whereas a probability sufficiently less than or greater than one-half would be suggestive of the profitability of a contrarian investment strategy and strength rule, respectively. However, it should be noted that this initial examination is very crude, as it says nothing about the size of subsequent movements, just the direction of such movements.

Cowles and Jones (1937) find that sequences outnumbered reversals with a resulting probability of 0.625, suggesting a random walk with drift and thus some structure in stock price movements. However, the authors find that the daily and weekly intervals are too short for movements to cover transaction costs. One month is found to be the optimum period but profits are modest. The evidence of structure in stock prices is perhaps the most important contribution of the paper.

Davidson and Dutia (1989) also find that there is a statistically significant positive relationship between abnormal returns earned in one year and the next. This pattern of winners keep on winning and losers keep on losing (‘momentum’ or ‘continuation’) forms the basis of the strength rule and poses a significant threat to the EMH, since the information content of performance in one period is not instantly and fully reflected in share prices before the next period (underreaction).

Evidence of return continuation is not confined to the US. Rouwenhorst (1998) finds that a medium-term momentum strategy executed on a diversified portfolio from 12 European equity markets over the period 1978-1995 generates an excess return of 1% per month (continuation is present in all 12 countries). Returns are robust to adjustment for risk and size and there is evidence that European and US momentum strategies have a common component. Further evidence of strong return momentum in developed European markets is provided by Doukas and McKnight (2005), Pan and Hsueh (2007) and Nijman *et al*. (2004). Rouwenhorst (1999) finds that emerging European markets also exhibit significant momentum.

There is abundant evidence of significant abnormal returns to momentum trading strategies in many other markets – both developed and emerging. For example, Hou and McKnight (2004), Kan and Kirikos (1996), and Kyrzanowski and Zhang (1992) present evidence of significant momentum returns in Canada.

Evidence of momentum in European markets has also been unearthed on an individual country basis for Italy (Mengoli, 2004), Sweden (Parmler and Gonzalez, 2007), Spain (Muga and Santamaria, 2009; Forner and Marhuenda, 2003) Switzerland (Rey and Schmid, 2007) and Germany (Schiereck *et al.* 1999; Glaser and Weber, 2003). Significant momentum returns are discovered in the UK by, *inter alios*, Siganos (2010); Galariotis *et al.* (2007); and Aarts and Lehnert (2005).

Studies that unearth evidence of momentum in a number of other developed markets include Huang (2006), Patro and Wu (2004), Bird and Whitaker (2003), Balvers and Wu (2006), Fong *et al*. (2004) and Griffin *et al*. (2005). Momentum in emerging markets is documented by Naranjo and Porter (2007), Muga and Santamaria (2007b), and van der Hart *et al.* (2003); while Shen *et al*. (2005) and Bhojraj and Swaminathan (2006) find strong evidence of momentum for both developed and emerging markets. Appendix A details the markets analysed by each of the above studies.

Researchers such as Schneider and Gaunt (2012), Phua *et al.* (2010), and Hurn and Pavlov (2003) document momentum in Australia, while Gunasekarage and Kot (2007) find supportive evidence for continuation in New Zealand. Significant strength rule returns are also documented in India (Ansari, 2012), China (Kang *et al*., 2002), Iran (Foster and Kharzai, 2008), Egypt (Ismail, 2012) and South Africa (Cubbin *et al.*, 2006).

The evidence of momentum is Asia is relatively weak with the positive momentum returns unearthed by Ramiah *et al.* (2011), Brown *et al.* (2008) and Naughton *et al.* (2008) contrasting with the findings of Hameed and Kusnadi (2002) and Ryan and Curtin (2006) that momentum is not profitable in a number of Asian markets. Furthermore, Cheng and Wu (2010) find that momentum profits are insignificant in Hong Kong; while Griffin *et al*. (2005) find that evidence of momentum is weak in East Asian markets. Du *et al.* (2009) and Fu and Wood (2010) show that momentum profits are weak or negative in Thailand and Taiwan, respectively.

Evidence of momentum is not confined to stock returns. Continuation has been documented in commodities markets (Miffre and Rallis, 2007) and currency markets (Okunev and White, 2003). Moskowitz *et al.* (2012) present evidence of momentum in equity index, currency, commodity, and bond futures. The authors document continuation over the 1-12 month time-frame followed by partial reversal over longer horizons consistent with behavioural theories of initial underreaction and delayed overreaction.

It is clear that the momentum anomaly is not unique to the US and unlikely to arise due to data mining. However, there is a shortage of research into the momentum anomaly in the four markets under review in this thesis. Several studies include stocks from the four markets but the majority construct portfolios using stocks from numerous markets. It is therefore not possible to adduce the returns at the country level in such studies. Table 2.1 presents the findings of studies that report separate results pertaining to one or more of the four markets in question.

Table 2.1

Findings in multi-market studies

The table provides a summary of the key findings relating to the four markets that are the focus of this thesis. Monthly (pm) or annual (pa) excess abnormal returns (with t-statistics in parentheses) and details of the rank and holding periods (in months) are presented where such details are reported in the relevant study.

Author(s)	**Market(s)**	**Rank, holding**	**Abnormal returns**
Doukas and McKnight (2005)	Denmark	6,6	0.0098 pm (3.30)
	Norway	6,6	0.0065 pm (1.40)
Griffin *et al*. (2005)	Denmark	6,6	High
	Greece		High
	Ireland		No details
	Norway		Low
Liu *et al.* (2011)	Denmark	12,6	0.77 pa (2.89)
	Norway		0.51 pa (1.33)
Naranjo and Porter (2007)	Denmark	11,1	0.73 pm (1.78)
	Ireland		1.01 pm (1.87)
	Norway		0.61 pm (1.15)
	Greece		1.46 pm (2.43)
Patro and Wu (2004)	Denmark	Various	Positive serial correlation
	Norway		Weaker evidence
Rouwenhorst (1998)	Denmark	6,6	0.0109 pm (3.16)
	Norway		0.0099 pm (2.09)
Van der Hart *et al.* (2003)	Greece	6,6	0.91 pm (2.30)

Historically, there has been a dearth of research into the momentum effect in Ireland. Two recent studies attempt to fill this void and document mixed evidence of momentum in returns. O'Sullivan and O'Sullivan (2010) show that momentum strategies with various numbers of stocks and rank and holding periods of varying lengths yield insignificant abnormal returns on Irish stocks.

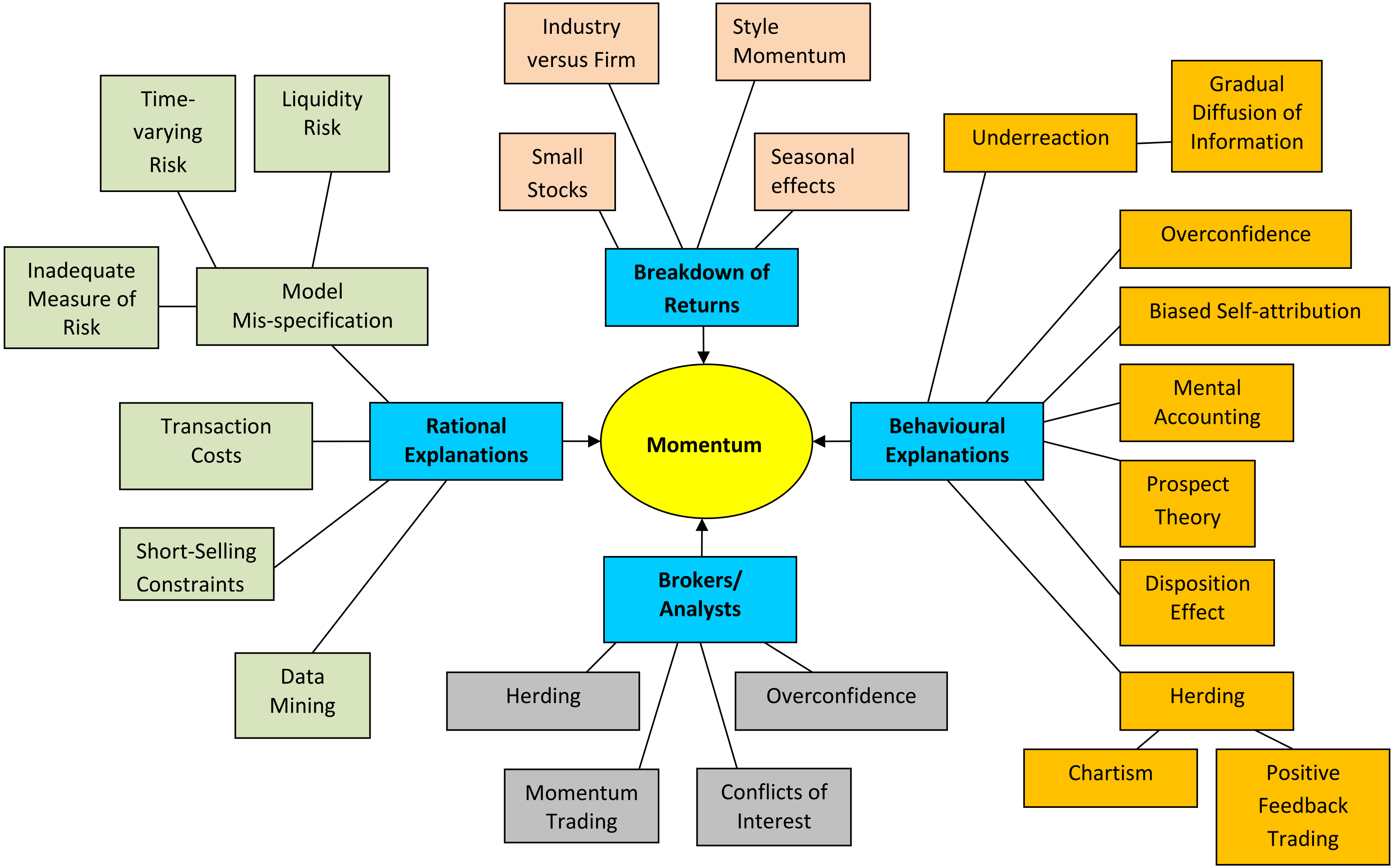
O'Donnell and Baur (2009) also show that a momentum strategy does not outperform the market index on the Irish market. However, a strategy of buying past winners alone yields economically and statistically significant abnormal returns. The most successful strategy involves ranking stocks over the past six months and holding the winners for the subsequent 12 months. Such a strategy generates 9.6% per month in excess of the market return. This shows that even investors without the ability to short sell can profit from momentum in returns.

2.3 Causes of momentum

While there is general agreement of the existence of a significant momentum effect there is considerable debate on the causes of such positive serial correlation in returns. Explanations can be broadly split into two camps; those that argue the effect is more apparent than real and can be explained by rational means, such as model mis-specification (Wu and Wang, 2005), transaction costs (Lesmond *et al.*, 2004), etc.; and those that argue that the effect is caused by irrational behaviour such as underreaction (Jegadeesh and Titman, 1993), overconfidence (Daniel *et al.*, 1998), etc. This highlights the joint-hypothesis problem, as excess abnormal returns for a particular investment strategy may not be an indication of market inefficiency or irrational behaviour but instead may be indicative of inefficiencies in the model used to compute abnormal returns. Figure 2.1 shows the main causes postulated to explain the momentum anomaly.

Figure 2.1

Causes of momentum



2.4 Rational explanations

Proponents of standard finance theory argue that the apparently anomalous evidence of return continuation is principally attributable to methodological flaws in research design. For example, Conrad and Kaul (1998) assert that momentum profits are attributable to cross-sectional variation in expected returns, rather than to predictable time-series variations in returns. Bulkley and Nawosah (2009) confirm this hypothesis by showing that momentum returns vanish when de-meaned returns are used.

In contrast, Jegadeesh and Titman (2001) argue that if Conrad and Kaul's hypothesis were true momentum profits should be similar in any post-ranking period. This is because Conrad and Kaul (1998) argue that stock prices follow random walks with drifts and that it is this (unconditional) drift that varies across stocks. Grundy and Martin (2001) test Conrad and Kaul's assertion and find that the momentum strategy generates excess returns of 9.24% per annum over the period 1966-1995 (using each stock as its own risk control).

When Jegadeesh and Titman (2001) extend their test period to five years they find that momentum returns increase monotonically for approximately one year and then decline for the following four years. The momentum strategy generates an average profit of 1.01% per month in the first year but registers losses ranging from 0.23 to 0.31% in years 2-5. Such findings are incongruous with the Conrad and Kaul (1998) hypothesis and are more consistent with the behavioural explanation that momentum profits will eventually reverse[7] (see Barberis *et al.*, 1998; Daniel *et al*., 1998; and Hong and Stein, 1999).

Jegadeesh and Titman (2002) argue that Conrad and Kaul's (1998) results are driven by sample biases, as they use bootstrap methods *with* replacement leading to the possibility that the same extreme returns are drawn in the rank and holding period, thereby suggesting momentum in returns. Jegadeesh and Titman (2002) show that cross-sectional differences in expected returns explain very little, if any, of the momentum profits.

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[7] Grundy and Martin (2001), and Megoli (2004) find similar results for the US and Italian markets, respectively.

2.4.1 Data mining

A criticism typically aimed at any study that claims to have unearthed a profitable trading strategy is that the results are attributable to data mining. Fama (1998, p.287) argues that "splashy results get more attention, and this creates an incentive to find them". Fama (1998) further states that an equal occurrence of overreaction and underreaction in entirely consistent with market efficiency as investors would be unable to determine which anomaly is more likely to prevail *ex ante*.

Furthermore, it is unlikely that cumulative excess returns to the momentum and contrarian strategies will always be zero. Therefore, if a momentum strategy generates large negative abnormal returns one could conclude that the contrarian investment strategy would be profitable. What is important from a market efficiency standpoint is that there is an equal chance of either one being successful in any given period.

Jegadeesh and Titman (2001) update their previous study by including the period 1990-98 in order to assess the out-of-sample validity of their findings. They also examine the momentum returns generated by small and large firms in order to assess whether the effect is unique to small illiquid shares. They find that the momentum strategy continues to generate positive excess abnormal returns of approximately 1.4% per month over the more recent period and momentum is not unique to small stocks. Thus, their original results do not seem to be attributable to data mining. The momentum profits are equally attributable to the buy (past winners) and sell (past losers) side of the strategy, contrary to the argument of Hong *et al*. (2000)[8].

Ji (2012) provides further evidence that momentum returns cannot be attributed to data mining by documenting significant strength rule returns using pre-CRSP data covering the period 1815-1925. As with much of the more recent evidence, Ji (2012) reports that momentum returns are negative in January and positive in all other months.

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[8] Hong *et al.* (2000) argue that most of the profits to the momentum strategy come from selling the past losers.

2.4.2 Model mis-specification

The principal mode of attack for proponents of EMH to any research that finds profitable strategies is on the methodological front. It is usually the treatment of risk that comes under the greatest scrutiny. It is argued that the anomaly is more apparent than real, as excess abnormal returns are a rational reward for risk or are a manifestation of the size and book-to-market effects.

However, Fama and French (1996) concede that their unconditional three-factor model cannot explain momentum profits. Their three factors proxy for risk (beta), firm distress (high minus low book-to-market) and the higher risk and lower liquidity of small firms (small minus large firm). Grundy and Martin (2001) run rolling regressions using the Fama-French three-factor model and find that risk-adjusted momentum returns are very close to, or actually higher than, raw returns. Thus, the Fama-French model does not seem to account for the excess returns to the momentum strategy. Indeed, Ahn *et al.* (2003) find that the Fama-French model actually magnifies raw returns.

Wu and Wang (2005) argue that the conventional procedure of running Fama-French three-factor regressions over the full sample period is inappropriate as it fails to account for the systematic dynamics of momentum portfolio factor loadings. Wu and Wang (2005) argue that using constant factor betas leads to an underestimation of the contribution of common risk factors to momentum profits. When the authors correct for this they find that 40% of the excess returns generated by individual stocks and almost 100% of those generated by style portfolios can be explained by the Fama-French three factors.

Carhart (1997) attempts to improve on the Fama-French three-factor model by adding a factor to capture the momentum anomaly and finds that his four-factor model is better able to explain time-series variation. Carhart (1997) evaluates the persistence in mutual fund returns (a test of the ‘smart money’ hypothesis) and finds that the majority of abnormal returns can be explained by one-year momentum (rather than stock picking abilities).

A failure to account for time-varying risk can explain apparently anomalous momentum returns. Li *et al*. (2008) find that good news and bad news have asymmetric effects on stock returns and on the conditional variance of stock returns (bad news increases the volatility of losers but has no significant impact on the volatility of winners). Failure to account for this would result in an under-estimation (over-estimation) of the volatility of losers (winners). Li *et al*. (2008) also document the strong impact of old news and the persistence of volatility for losers (half-life of over three years) and argue that it is due to managers' reluctance to release bad news (especially those of companies with low analyst coverage). The opposite is true for winner stocks. Thus, not only does bad news travel slowly, as argued by Hong *et al*. (2000), but good news travels quickly[9].

Li *et al*. (2008) conclude that momentum 'profits' are merely a compensation for time-varying unsystematic risks (common to both winner and loser stocks); thus the EMH holds. The 'profits' disappear when a Generalised Autoregressive Conditional Heteroscedasticity (GARCH) model is used; largely because of an increase in the returns of the loser portfolio. This suggests that the poor performance of the loser portfolio using models based on static risk was in part due to their sluggish and asymmetric reaction to bad news.

Du and Denning (2005) also assert that standard models, such as the CAPM and the Fama–French three-factor model, fail to fully measure the common factor risk due to the delayed reaction to common factors. By including the lagged Fama–French factors the authors find that industry momentum is mainly due to the common factors, not industry-specific idiosyncratic risk. However, Lewellen and Nagel (2006) find that the conditional CAPM cannot explain asset-pricing anomalies such as momentum. The authors find little evidence that betas covary with the market risk premium in such a way as to explain the alphas of the momentum portfolio and find that conditional alphas are large, statistically significant, and close to the unconditional alphas.

Karolyi and Kho (2004) use bootstrap techniques to examine whether a number of return-generating models that allow for time-varying expected returns can explain momentum.

[9] In contrast, McQueen *et al.* (1996) find that stocks react slowly to good news but quickly to bad news.

Although none of the models used are capable of generating returns as large as the actual momentum profits, Karolyi and Kho (2004) find that 75-80% of such profits can be explained by market-wide and macroeconomic instrumental variables.

Blitz *et al.* (2011) argue that conventional momentum strategies simply bet on the continuation of the reward to Fama-French factors, as in market upturns winner stocks are likely to have high betas and book-to-market ratios. Ranking stocks on residual returns neutralises such dynamic factor exposures. Blitz *et al.* (2011) show that momentum strategies formed conditional on residual returns earn risk-adjusted returns of approximately twice the order of those formed on total returns. Residuals are calculated using the Fama-French three-factor model, suggesting that the profits are not driven by risk factors. Furthermore, Blitz *et al.* (2011) show that residual momentum profits are consistent over different time periods and economic states, and are not driven by small-firm or seasonal effects that often plague conventional momentum strategies. This suggests that momentum returns are not driven by microstructure biases, data mining, and risk.

Similarly, Fong *et al*. (2005) examine the momentum strategy at country level for 24 nations and find that the momentum strategy generates positive excess abnormal returns after accounting for risk and transaction costs regardless of the economic state and sub-period analysed. The authors conclude that momentum profits are more likely to be attributable to irrational behaviour than to omitted risk factors.

2.4.3 Liquidity risk

It is possible that the superior returns to momentum strategies are merely a reward for additional liquidity risk. Sadka (2006) finds that up to 83% of the cross-sectional variation in momentum portfolios can be accounted for by liquidity risk. Sadka (2006, p.311) argues that since the variable component of liquidity risk can be associated with private information then a significant proportion of momentum profits can be attributed to "compensation for the unexpected variations in the aggregate ratio of informed traders to noise traders and the quality of information possessed by the informed traders".

Pástor and Stambaugh (2003) find that a liquidity risk factor accounts for over half of the profits of the momentum strategy, while Chang (2005) finds that liquidity risk (primarily that of losers) accounts for up to 82% of the cross-sectional variation in momentum portfolios and subsumes the momentum magnifying effects. Similarly, Bhootra (2011) shows that momentum profits significantly decrease when stocks priced less than $5 are excluded.

2.4.4 Transaction costs and short-selling constraints

Momentum strategies involve high portfolio turnover, often in small stocks; thus transaction costs can often be prohibitive. Furthermore, short selling is not always possible. Thus, apparently profitable investing opportunities can survive the process of arbitrage. Lesmond *et al*. (2004) assert that previous studies documenting significant momentum profits (such as Jegadeesh and Titman, 1993) under-estimate transaction costs. Lesmond *et al*. (2004) argue that momentum strategies require frequent trading in particularly costly stocks to such an extent that most 'profits' found in previous studies would be swamped by transaction costs if such costs were measured correctly.

Lesmond *et al*. (2004) re-assess the returns to the momentum strategy documented by Jegadeesh and Titman (1993 and 2001) and Hong *et al*. (2000), albeit for a different time period (1980-1998). The strategy is found to produce significant 'paper profits' ranging from 0.45% to 1.30% per month. The majority of the trading returns (ranging from 53% to 70%) are generated by short selling the loser portfolio. Lesmond *et al*. (2004) characterise such stocks as small, low price, high beta, and off-NYSE stocks. It is also found that such stocks have low liquidity. It can thus be expected that the trading costs involved with these stock would be high.

Lesmond *et al*. (2004) use four methods to estimate trading costs and find that in almost all cases such costs exceed the paper profits of the relative strength rule strategy. The authors find that trading costs for large capitalisation stocks generally vary from 1% to 2%, whereas for small capitalisation stocks trading costs are between 5% and 9%[10]. The momentum strategy produced significant profits after trading costs on only one occasion. Furthermore, the standard deviation of returns of the Jegadeesh and Titman (1993) strategy is 7.8%, with returns varying from -49% to +32%. Thus, the EMH holds in the sense that it is not possible to consistently make excess abnormal returns (after accounting for transaction costs) using past information.

However, Jegadeesh and Titman (2001) conclude that the argument that momentum profits should disappear for larger stocks (but not for smaller ones due to transaction stocks) is not supported by their data. The profits from trading in past winners are not eliminated to a greater degree than those of past losers[11].

The probability of the momentum strategy generating positive post-cost abnormal returns increases when one uses a relatively long holding period and focuses on low transaction shares. Agyei-Ampomah (2007) shows that only momentum strategies with holding periods greater than six months are capable of generating statistically and economically significant post-cost returns, while Li *et al*. (2009) generate similar returns when concentrating on low transaction-cost shares. Rey and Schmid (2007) show that significant post-cost returns can be generated by focusing solely on large capitalisation companies.

Siganos (2010) finds that even small investors can profit from momentum in shares after accounting for transaction costs. This is achieved by using a relatively small number of firms to form the winner and loser portfolios and by utilising a relatively long holding period (at least six months) in order to minimise transaction costs. Siganos (2010) finds that it is optimum for an investor to hold 20 winners and 20 losers. Hanna and Ready (2005) also show that momentum profits are robust to austere specfications of transaction costs. In contrast, Trethewey and Crack (2010) show that transaction costs swamp momentum returns in New Zealand.

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[10] However, Chan and Lakonishok (1995) estimate the trading costs for small firms to be only 3%.
[11] Similar findings can be found in Korajczyk and Sadka (2004).

Li *et al.* (2009) find that round-trip transactions costs for selling loser firms are approximately double those of buying winners and this is even more pronounced for low-volume stocks. The costs of buying winners and losers are more similar, irrespective of volume levels. However, in net terms momentum strategies remain more profitable when based on low volume stocks.

In addition to restrictive transaction costs, the need to short sell securities can prevent individual investors from exploiting any anomaly. Short-sale constraints are particularly salient in view of the dominant contribution of the loser portfolio to momentum returns in the majority of studies. Alexander (2000) shows that many studies that use 'zero investment' strategies are biased towards rejecting market efficiency as they ignore such constraints. Barber and Odean (2008) find that only 0.29% of individual traders take short positions, while Chen *et al.* (2002) find that the majority of stocks have virtually no short interest outstanding at any given point of time and Sadka and Scherbina (2007) and Jones and Lamont (2002) find that overpriced stocks tend to be expensive to short. Ali and Trombley (2006) find that momentum returns are dominated by the loser portfolio but short-sale constraints prevent arbitrage of these returns.

Market frictions such as bid-ask spreads, short-selling constraints and illiquidity are more pronounced in small and emerging markets. De Roon *et al*. (2001) find that anomalous returns in recently liberalised emerging markets cannot be exploited due to short-sale constraints and transaction costs. Ghysels and Cherkaoui (2003) find that transaction costs are prohibitively high on the Casablanca stock exchange.

However, short-sale constraints and transaction costs do not necessarily prevent investors for exploiting return continuation. Griffin *et al.* (2005) investigate momentum in 40 countries and show that small investors can profit from momentum without the need to take short positions. Fong *et al*. (2005) reach the same conclusion when studying momentum in 24 countries, finding that buying past winners generates significant abnormal returns after transaction costs[12]. Muga and Santamaria (2007b) show that transaction costs and risk are incapable of explaining the significant momentum returns in four South American markets (Argentina, Brazil, Chile, and Mexico); while Phua *et al.* (2010) show that momentum returns in Australia are mainly attributable to past winners. Boynton and Oppenheimer (2006) show that momentum returns increase when survivorship bias and bid-ask spreads are accounted for.

2.5 Macroeconomic variables

Chordia and Shivakumar (2002) find that momentum profits can be explained by lagged macroeconomic variables linked to the business cycle, such as inflation. The authors argue that momentum returns may be attributable to time-varying expected returns as opposed to behavioural explanations. Karolyi and Kho (2004) find that 75-80% of momentum profits can be explained by market-wide and macroeconomic instrumental variables. O'Sullivan and O'Sullivan (2010) and O' Donnell and Baur (2009) find that momentum strategies in Ireland generate more significant returns in periods of higher market growth.

Cheng and Wu (2010) show that momentum profits in Hong Kong become insignificant when macroeconomic variables are taken into account. However, Griffin *et al*. (2003) find that macroeconomic risk cannot explain momentum profits and show that such profits are large and significant in good and bad economic states. The finding of Griffin *et al*. (2003) that momentum profits reverse over one- to five-year horizons is more consistent with behavioural rather than risk-based explanations of momentum.

Griffin *et al*. (2003) find that momentum profits tend to be larger in bear markets in the US, while Rey and Schmid (2007) reach a similar conclusion using Swiss data. However, these findings are contradicted by Ismail (2012), Avramov *et al.* (2007), and Bird and Whitaker (2003), who show that momentum strategies only generate economically significant results in bull markets. Cooper *et al*. (2004) find that mean monthly momentum profits are 0.93% after

[12] These findings may explain the results of Lakonishok *et al*. (1991) and Wermers (1999) who report that fund managers and mutual funds buy past winners but do not sell past losers.

positive market returns, compared to -0.37% following down markets. Huang (2006) largely confirms the findings of Cooper *et al.* (2004) using Morgan Stanley Capital International (MSCI) index monthly returns for 17 countries. Du *et al.* (2009) show that momentum profits are negative in Thailand after down markets.

In contrast, Siganos and Chelley-Steeley (2006) find that momentum returns are stronger *following* bear markets in the UK. Muga and Santamaria (2009) find that momentum returns are significantly positive in Spain following both up and down market states. Furthermore, momentum was stronger for long holding periods following down markets. Thus, one cannot necessarily draw a conclusive link between momentum returns and market state.

2.6 Behavioural theories

The failure of rational models to fully account for momentum profits has led many researchers to turn to behavioural explanations of the anomaly. Behavioural Finance (BF) represents an eclectic approach where finance collaborates with social sciences such as psychology and sociology. BF has gained increasing favour over recent decades as an alternative paradigm to standard finance theory. In essence, BF relaxes the assumptions of rationality employed by standard theory, in light of a considerable body of evidence from the field of cognitive psychology suggesting that agents are irrational and systematically make errors in processing information. As Albert Einstein said: “Two things are infinite: the universe and human stupidity; and I'm not sure about the universe.”

BF recognises the importance of ‘greed and fear’ and ‘animal spirits’ and shows that investors are influenced by a myriad of psychological factors such as mood, affect, previous gains, loss and regret aversion, anchoring, framing, overconfidence, optimism, and herding. Crucially, BF has adduced evidence that such biased behaviour has a material impact on share prices, often in a systematic manner, in violation of the standard finance theory. One of the main tenets of behavioural finance is the theory of noise traders.

2.6.1 Noise traders

Shefrin and Statman (1985) assert that noise traders are the drivers of all stock market anomalies. The theory of 'noise traders' was principally developed by Poterba and Summers (1988), building on the work of Shiller (1984) and Black (1986). De Long *et al.* (1990b, p.706) describe noise traders as individuals who "falsely believe that they have special information about the future price of risky assets". In essence, noise traders are individuals whose demand for shares is determined by factors other than their expected return. It is of great interest to establish whether such traders can affect stock prices and market efficiency.

Long before the term 'noise trader' was coined, Keynes clearly recognised the predilection of individuals to act on impulse rather than information. Keynes (1936, p.161-162) states that "a large proportion of our positive activities depend on spontaneous optimism rather than mathematical expectations" and further argues that prices are driven by 'animal spirits' rather than "as the outcome of a weighted average of quantitative benefits multiplied by quantitative probabilities". Keynes (1936, p.154) also states that prices may be influenced by the "mass psychology of a large number of ignorant individuals" and may fluctuate suddenly due to "waves of optimistic and pessimistic sentiment" caused by "factors which do not really make much difference to the prospective yield".

The theory of noise traders attempts to explain the excessive volatility puzzle as it posits that investors trade even if they lack any pertinent information relating to a company's fundamental value. Cutler *et al.* (1989) show that there is only a weak relationship between news and trading volume. Black (1986) explores the impact of 'noise' on finance, econometrics, and macroeconomics and concludes that trading in financial markets is made possible by noise. Furthermore, noise results in markets being somewhat inefficient but can simultaneously prevent investors taking advantage of such inefficiencies. Shiller (1984) develops a model of investor sentiment where the interaction between 'smart-money investors' and 'ordinary investors' (who overreact to news or are vulnerable to fads) leads to overreaction.

In relation to financial markets, Black (1986) uses the word ‘noise’ as being the opposite of information. Some investors trade on information, whereas others trade on noise (in the mistaken belief that it is information). Noise trading is essential if markets are to be liquid, as if every investor had perfect information no two investors would take opposing positions. This is linked to the Grossman-Stiglitz paradox (1980), as Black (1986) explains that not only must noise traders exist but/or investors who trade on information must think that there are noise traders and be able to identify them. If they are contemplating trading on information then they will need to examine the counterparty trader. If the counterparty is an information trader then the original trader may not be willing to trade, as they cannot be confident as to whose information is more accurate. On the other hand, an information trader would be much more confident of ‘out-smarting’ a noise trader.

The above suggests that noise traders should not trade (apart from perhaps with other noise traders). However, Black (1986) assumes that they will trade in the belief that they do actually possess information. Noise trading may cause share prices to move away from their fundamental values (the price that is based on perfect information with no noise); thereby leading to market inefficiency. On most occasions information traders will make money at the expense of noise traders.

Perhaps the most important argument put forward by Black (1986) is that information traders will not trade to the extent that they drive noise traders from the market and thus ensure efficiency. This conclusion is reached because information traders have an edge on noise traders but no guarantee that their information is correct (how is their *ex-ante* belief that they are information traders different from that of noise traders?). Taking larger positions involves taking greater risks and traders can never be certain that their ‘information’ is not ‘noise’.

Furthermore, the information that they possess may be incorporated into share prices already due to the trading of equally-informed traders. Afterall, they do not necessarily have a monopoly on any piece of information. Trading on such information has the same effect as trading on noise and may explain apparent investor overreaction (Arrow, 1982). However, Black (1986) argues that, over time, information traders become aware that share prices are moving away from their fundamental values and will thus trade aggressively to bring them back. Thus, prices will be mean-reverting in nature.

Black (1986) concludes that noise traders create the opportunity for information traders to make profits by trading but equally make it difficult for them to do so. This is accentuated by the fact that in calculating the fundamental value of a firm, investors usually multiply earnings by a suitable price-earnings ratio. Since price may have a noise component in it then so too will the value of the firm through the price-earnings component of the valuation

The perils facing rational investors in betting against noise traders were clearly outlined by Keynes (1936, p.157), who argued that investors who attempt to rationally forecast the long-term value of securities "run greater risks than he who tries to guess better than the crowd how the crowd will behave". Keynes (1936, p.157) also outlined the limits of arbitrage when arguing that "markets can remain irrational longer than you can remain solvent" as "an investor who proposes to ignore near-term market fluctuations needs greater resources for safety and must not operate on so large a scale, if at all, with borrowed money".

Shleifer and Summers (1990) base their 'noise trader approach to finance' on two assumptions. First, some investors ('noise traders') are not fully rational and their beliefs are not completely explained or justified by fundamental news. The remaining investors ('arbitrageurs') form rational expectations about security returns. Second, arbitrage is both risky and limited because of principal-agent problems. The combination of the two assumptions implies that changes in investor sentiment is not fully countered by arbitrageurs and thus affects security returns. Therefore, there is no guarantee that a rational-expectations equilibrium will result.

Shleifer and Summers (1990) posit that the opinions and trading patterns of noise traders may be subject to systematic biases. In the absence of limits to arbitrage the actions of arbitrageurs would correct any noise introduced into stock prices and ensure that they return to their fundamental value as argued by Friedman (1953) and Fama (1970). However, in reality there are two types of risk that may limit arbitrage and thus provide an alternative to the efficient market hypothesis approach to finance.

The first is fundamental risk. In essence short selling ‘overvalued’ stocks is risky because there is always a chance that the market will increase, thereby driving prices even higher. Fear of this prevents an arbitrageur from short selling and driving prices down to their fundamental values. The second risk stems from the unpredictability of the future resale price of the stock in question. Future mispricing may become even more extreme and the fear of this puts a limit on arbitrage. No trader wants to be the first to sell a stock for fear that it will increase even further.

Furthermore, arbitrageurs have short horizons, as the performance of most money managers is periodically evaluated. This results in a myopic perspective and the structure of transaction costs also induces a bias towards short horizons because arbitrageurs have to borrow to implement their trades and fees cumulate over time. Thus, long-term arbitrage opportunities may persist (Shleifer and Summers, 1990).

Crucially, the above limits of arbitrage are actually understated as it is assumed that the arbitrageur knows the fundamental value of the security. It has been shown that a time series of share prices that deviate from fundamental values looks extremely like a random walk and thus an arbitrageur may not be able to identify/quantify any mispricing.

Shleifer and Vishny (1997) focus on the ‘limits of arbitrage’ caused by the agency problem. Arbitrageurs (agents) are less likely to receive funds from investors (principals) when prices deviate substantially from their fundamental values since in such a situation arbitrageurs would have performed poorly. Thus, arbitrage is limited and in situations where there is the greatest opportunity for an arbitrageur to profit from mis-pricing the arbitrageur is least able to obtain the necessary funds to do so. Pontiff (1996) confirms this theory empirically.

Gallagher and Taylor (2001) examine the speed of reversion of the market log dividend-price ratio for U.S data and find that Shleifer and Summers’ (2000) theory of risky arbitrage is better able to explain the lack of arbitrage than the limits of arbitrage model of Shleifer and Vishny (1997).

Russell and Thaler (1985) conclude that if there are some 'quasi-rational' agents in an economy, then a rational-expectations equilibrium is not guaranteed despite the existence of some rational agents. Market efficiency is less likely when noise traders are continually entering the market and prices may diverge from their fundamental values, at least for short periods. Palomino (1996) shows that noise traders are more likely to survive in small markets.

De Long *et al.* (1990b) develop a model where noise traders not only affect share prices but also earn higher expected returns than rational investors. Noise traders introduce additional pricing risk and the inability of arbitrageurs with short horizons to predict noise traders' beliefs deters them from trading aggressively against such traders. Noise traders thus make returns from the risk that they create and they survive the process of arbitrage.

Changes in investor demand for securities are not always rational. Sometimes they are caused by changes in expectations or sentiment unrelated to information. They may also be caused by trend chasing and other trading strategies. Subjects in psychological experiments tend to make systematic as opposed to random mistakes. If all people make the same predictable mistakes then such mistakes become cumulative rather than self-cancelling.

Furthermore, technical analysis (or 'chartism') is based on noise, rather than on information. Friedman (1953) argues that such noise traders will not survive as they will lose money and their reduced wealth will mean they have a smaller effect on demand. It has also been argued that noise traders will learn from their errors and transform themselves into rational arbitrageurs over time. Shleifer and Summers (1990) disagree with both of these arguments.

First, noise traders can earn higher expected returns if they take on more risk and this risk is rewarded by the market. Second, if noise traders get 'lucky' and make a positive return this may both encourage them to take even more risks believing their success was due to skill rather than luck and may also encourage new traders to imitate their strategies, thereby increasing the number of noise traders in the market. In effect, most noise traders can be expected to lose money but a small proportion may win and thus influence share prices even in the long run. Furthermore, Kogan *et al*. (2006) show that irrational traders can have a significant effect on prices even as their wealth falls towards zero in the long run.

Shleifer and Summers (1990) further state that when arbitrageurs bet against noise traders they begin to look like noise traders themselves. Often, they do not pick stocks on the basis of fundamentals or for diversification purposes but simply bet against noise traders. Arbitrageurs often follow contrarian strategies and it can become difficult to differentiate between noise traders and arbitrageurs.

Hirshleifer *et al*. (2006) develop a model in which the trading activity of noise traders affects prices and cash flows. Hirshleifer *et al*. (2006) argue that all such investors are eventually endowed with the same sentiment. What is important is the timing of such an endowment. Some irrational traders are endowed with it earlier and thus able to trade before others giving them a first-mover advantage. In this setting, momentum is likely as irrational investors buy (or sell) shares for a number of consecutive trading days. The early traders are able to make a profit at the expense of the slow starters.

It may be expected that this momentum will be followed by a reversal of a similar magnitude. However, if there is feedback from share prices to cash flows (as argued by Hirshleifer *et al*., 2006) then the effect is not completely negated and irrational traders as a group can make excess returns from trading. This is because the gains of the early irrational traders outweigh the losses of the late traders.

2.6.2 Positive feedback trading and technical analysis

Noise traders often engage in positive feedback trading. This is a form of trend chasing where investors buy stocks after they rise and sell stocks after they fall. Such a strategy may be pursued in the belief of the existence of underreaction or as a way of initiating a bandwagon effect or speculative bubble. Goetzmann and Massa (2001) analyse the trading patterns of 91,000 investors and find that investors tend to habitually behave as positive feedback traders or contrarians and rarely shift from one category to the other.

It should be remembered that in order to make profits from trading, investors should not be overly concerned with predicting the fundamental value of a stock but rather in predicting the behaviour of other investors. It may thus be in their interest to act like a noise trader, as forecasting share prices is analogous to forecasting the winner of a Keynesian 'beauty contest'[13]. Graham and Dodd (1934) cogently capture the essence of the price discovery process when arguing that:

> The market is not a weighing machine, on which the value of each issue is recorded by an exact and impersonal mechanism. Rather the market is a voting machine, whereon countless individuals register choices which are the product partly of reason and partly of emotion (p.23).

When a sufficient number of investors follow positive feedback strategies it may become beneficial for arbitrageurs to jump on the bandwagon rather than attempt to buck the trend. The effect of arbitrage in this case is to stimulate the interest of other investors and thus have a destabilising effect, as prices move even further away from their fundamental values.

This kind of attitude ('if you can't beat them, join them') may explain the overreaction phenomenon. Prices will eventually go so far out of line with fundamentals that they will begin to reverse. It could be argued that when arbitrageurs get involved in this way it may increase the positive feedback that noise traders receive. In believing that their views were correct, they may increase their trades. The prophecies of noise traders in that sense may become self-fulfilling in nature.

Although the approach and conclusions of Black (1986) and Shleifer and Summers (1990) are similar they differ in one important respect. Black (1986) feels that share prices are mean

[13] According to Keynes (1936, p.154), professional investors should be concerned "not with what an investment is really worth to a man who buys it 'for keeps', but with what the market will value it at, under the influence of mass psychology, three months or a year hence."

reverting in the long run, whereas Shleifer and Summers (1990) feel that sufficient resources will not be put into stocks to bring them back to their fundamental values in the long run. However, it should be noted that fundamental value and mean reversion are not necessarily the same thing. The mean of a stock is not necessarily its fundamental value, although the terms are often used interchangeably.

The noise trader approach provides an alternative explanation of the phenomenon of continuation followed by subsequent reversal as found by, *inter alios*, Poterba and Summers (1988) and Jegadeesh and Titman (1993). Such findings may not arise as a result of underreaction and overreaction but instead may be rooted in deeper psychological causes such as overconfidence, recency hypothesis, hot-hand hypothesis, loss aversion, regret, and bandwagon effects. In effect, arbitrageurs may be inclined to originally act like noise traders, thus accentuating positive autocorrelation before eventually acting like true arbitrageurs and initiating reversal in accordance with the mean-reversion hypothesis (De Long *et al.*, 1990a).

Brozynski *et al*. (2003) present survey evidence on the use of contrarian, momentum, and buy-and-hold strategies by fund managers in Germany. The authors find that the momentum strategy is widely used (more than 90% of respondents use it to some degree) due to its excess returns (in a relatively short period compared to the contrarian investment strategy), in addition to its avoidance of positions that are against market trends. Grinblatt *et al*. (1995) report a similar finding for American fund managers and additionally show that managers only use momentum strategies after good news, buying past winners but not short selling past losers.

Keim and Madhavan (1995) find that the number of institutional traders acting like contrarians and momentum traders is approximately equal and suggest that the effect may thus be offsetting. Similarly, Brozynski *et al*. (2003) find that fund managers do not tend to use either strategy exclusively; the correlation coefficient on the use of the two strategies is 0.344, suggesting that many fund managers use both methods.

Gutierrez and Prinsky (2007) assert that the incentives of trading institutions induce them to chase relative returns and underreact to firm-specific abnormal returns. They show that momentum persists for a number of years without reversing, consistent with underreaction. They find that institutions aggressively buy stocks with the highest prior returns and avoid stocks with the lowest prior returns.

Keim and Madhavan (1995) show that institutional traders behave asymmetrically with respect to buy and sell orders. Traders take longer to execute buy orders than equivalent-sized sell orders. Furthermore, the duration of trading increases with order size, liquidity, and market capitalisation. This delayed execution of trades may explain short-term momentum in past winning stocks. Traders may appear to be momentum traders but may in fact be trading sequentially on their own private information. Furthermore, Keim and Madhavan (1995) show that contrarian investors in some institutions focus solely on buying past losers.

He and Shen (2010) show that investors form extrapolative return and earnings expectations based on past market and price returns. Such expectations appear to be over-optimistic (over-pessimistic) for stocks with extremely high (low) returns in the previous year. These findings remain after controlling for risk and analyst optimism and lend support, using real market data, to the findings from experimental research[14]. This evidence of a positive relationship between past and expected returns suggests that investors trade based on momentum, driving prices beyond their fundamental value; thereby necessitating a reversal in order to realign prices with their fundamental values.

The idea that overreaction is caused by self-fulfilling prophesis and positive feedback trading is examined by Lynch (2000) in the context of 'thought contagion'. Thought contagion builds on the idea of memes as developed by Richard Dawkins and is a theoretical paradigm that focuses on the evolutionary epidemiology of ideas. It refers to ideas that stimulate their host to proselytise their worth, thereby propagating their re-transmission. The theory of how

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[14] See, for example, Shefrin (2005), Caginalp *et al.* (2000), and De Bondt (1993), who document a strong positive correlation between investors' expected returns and past returns.

some ideas become widely accepted, regardless of their accuracy, is of importance to the behaviour of stock prices.

Lynch (2000) argues that momentum in returns may occur because of such thought contagion. If a share performs well over a specified period current investors in the share are more likely to talk about their holdings in the share as they are proud of their success and/or may want to encourage others to buy the share to further inflate its price. Potential investors may jump on the bandwagon and push the share price beyond its fundamental value.

Investors need not believe that their share purchase is rational in terms of the fundamental value of the share. Instead, they may hope that the current positive contagion (bubble) attached to the share facilitates a subsequently profitable sale to a 'greater fool'. The speed of on-line communications and the role of brokers in co-ordinating public opinion have increased the importance of such thought contagion in recent decades. Such contagion was concisely observed in the Internet bubble and the doomsday prophecy surrounding the Y2K computer bug. Rumours regarding potential takeovers and stock recommendations can also fuel such overreactions, which manifest themselves in herding behaviour[15].

Shi *et al.* (2012) show that positive feedback trading, and consequently momentum returns, are higher for firms with extreme past returns. Such feedback trading is approximately twice as pronounced in the case of past losers than winners. The link between positive feedback trading and momentum returns is higher for stocks with high information uncertainty, consistent with noise trading models.

The effects of positive feedback trading may be accentuated by herding, which co-ordinates the actions of investors (see for example Hwang and Salmon, 2004). In the presence of intentional herding investors ignore their private information[16]. Accordingly, share prices

[15] For a more detailed discussion on the importance of fads, information cascades, and bubbles, see for example, Shiller and Pound (1989); Welch (1992); and Bikhchandani *et al.* (1998).

[16] It is important to distinguish between intentional herding and what Bikhchandani and Sharma (2001) refer to as 'spurious' herding. The former arises when individuals choose to follow the actions of others, whereas the latter refers to a situation where individuals act independently but take similar actions based on fundamentals. Whether herding is coincidental or correlated has important implications for market efficiency.

may not accurately reflect all available information and may move away from their fundamental values. This can result in momentum followed by reversal (bubbles and subsequent crashes), as information gradually cascades and prices revert towards their means. Herding by analysts is particularly important and will be examined in section 4.6.

2.6.3 Underreaction to news

A prominent school of thought suggests that momentum is caused by investors underreacting to news, causing prices to drift rather than instantly adjust towards their fundamental values. The terms 'underreaction' and 'overreaction' are synonymous with return momentum and reversal, respectively. However, the momentum anomaly may arise as a result of either of the two information-processing errors. The dynamics of share price vis-à-vis the stock's fundamental value are of seminal importance in correctly labelling the anomaly. Underreaction occurs when prices react insufficiently to company-specific news causing positive serial correlation that gradually results in the share price adjusting towards its fundamental value.

Alternatively, if prices exhibit positive serial correlation but overshoot their fundamental value, one can say that the market has overreacted. This is observed when overreaction occurs sequentially due to the delayed response of, and/or the asynchronous release of brokers' recommendations to, various groups of investors. When overreaction occurs in this manner one observes positive serial correlation in returns and this is often interpreted as underreaction. If overreaction occurs in a more contemporaneous manner then it will be correctly interpreted, *ex post*, as an overreaction if and when prices revert. Naturally, one can also observe underreaction followed by overreaction; however, the automatic labelling of positive serially correlated returns as evidence of underreaction is flawed.

Additionally, momentum in stock prices may occur from a rational and prompt response to a series of news events of the same category. Outside a laboratory setting, it is impossible to isolate one key news event. Consequently, momentum in returns can be misinterpreted as underreaction. In the presence of sequentially conflicting news, the labelling of contrarian returns as overreaction may represent a similar misnomer.

However, the above rational explanation may not be apposite if one unearths consistent evidence of momentum or reversal, as one may expect that good and bad news are serially independent. A notable exception is when companies engage in earnings management in order to continually beat EPS targets. In the presence of such manipulation of earnings, good news may be serially correlated, thereby rendering positive serial correlation in returns rational. It can also be argued that a vicious or virtuous cycle of news can be propagated by the two-way link between share prices and fundamentals. Changes in share price can affect a company's credit rating, collateral, gearing, and cost of capital, which can have reinforcing effects on share price, thereby increasing the likelihood of good (bad) news in successive periods (Soros, 1998).

Jegadeesh and Titman (1993) decompose the profitability of the strength rule and find that it is not explained by systematic risk, which would be consistent with efficient markets or delayed stock price reactions to common factors. They find that the profits are best explained by delayed price reactions to firm-specific information (market underreaction), implying market inefficiency, as prices are not quickly and fully adjusting to new information. Jegadeesh and Titman (1993) find that returns reverse in the longer term, with approximately half of the momentum profits earned in the past six months dissipating over the subsequent 24 months.

Lee and Swaminathan (2000) and Jegadeesh and Titman (2001) confirm these findings. However, Nagel (2001) shows that these apparent long-term reversals can be accounted for by a book-to-market effect. Chan and Kot (2002) argue that the time frame that defines past losers and winners is a key determinant of the extent of momentum profits. They find that a momentum strategy that buys stocks that are short-term winners but long-term losers and sells stocks that are short-term losers but long-term winners produces increasing profits for up to 60 months. Their adjusted momentum strategy in essence attempts to combine the returns from the documented short-term momentum and long-term reversal in stocks.

A key example of market underreaction is the phenomenon of post-earnings announcement drift (PEAD), which Fama (1998, p.286) labels the "granddaddy of underreaction events". Ball and Brown (1968) find that after an earnings announcement the abnormal returns of good (bad) news firms tend to remain positive (negative) for a period of time greater than that predicted by the EMH. Returns tend to drift rather than rapidly adjust to their new levels after an earnings announcement.

In one of the earliest documented event studies, Ashley (1962) shows that stock prices react more quickly to bad news than good news. Ashley (1962) also presents evidence of drift after earnings and dividends announcements. Bernard and Thomas (1989) find that PEAD is more likely to be caused by delayed response to new information than by model mis-specification or transaction costs. Such a finding is supported by Chan *et al*. (1996), who show that a portion of momentum profits in the US can be attributed to underreaction to earnings information, but price momentum is not subsumed by earnings momentum.

Chan *et al*. (1996) show that sorting stocks by their prior six-month returns (earnings revisions) generates excess returns of 8.8% (7.7%) over the subsequent six months. Momentum returns are not explained by market risk, size, and book-to-market effects but are more likely caused by analysts' sluggish response to news. If the market is surprised by an earnings announcement it tends to be surprised in the same direction for at least the next two earnings announcements; thus forecasts are revised sluggishly and new information is assimilated slowly. Analysts are particularly slow to revise estimates downwards, possibly due to conflicts of interest.

Van Dijk and Huibers (2002) confirm the results of Chan *et al*. (1996) for European markets, finding that analysts underreact to new earnings information and are slow to revise their earnings forecasts. Such undereaction causes positive autocorrelation in earnings revisions, which in turn causes positive autocorrelation (momentum) in prices. Van Dijk and Huibers (2002) find that the momentum strategy generates an average excess abnormal return of more than 10% per annum in the 15 countries studied. Consistent with Chan *et al*. (1996), the momentum effect is shown to be distinct from the value and size effects.

Hong and Stein (1999) examine the gradual diffusion of information by assuming that there are two types of investors; news watchers and momentum traders. The former group are only interested in fundamental information and ignore past prices, whereas the latter behave in the opposite manner. The authors argue that it is the gradual diffusion of information among the news watchers that leads to market underreaction and thus momentum profits. The momentum traders (technical analysts) then extrapolate based on past prices, pushing the prices of past winners above their fundamental values. Both sets of investors in this model update their expectations in a rational manner but only use partial information, thereby leading to return predictability. Investors are unable to extract the private information of others from prices.

Hong *et al*. (2000) test this gradual information diffusion model using firm size and analyst coverage as proxies for the rate of information diffusion and find that the momentum effect is only present for smaller firms and is more prevalent for firms with low analyst coverage (especially for past losers). Verardo (2009) also shows that momentum returns are positively correlated with dispersion in analysts' forecasts and Doukas and McKnight (2005) provide out-of-sample confirmation of the negative relationship between momentum returns and analyst coverage. Such findings are consistent with the gradual diffusion of firm-specific information, especially negative information. These findings are confirmed for emerging markets (Wen, 2005) and European markets (Doukas and McKnight, 2005). Furthermore, Hou and McKnight (2004) find that analyst coverage is the main driver of momentum profits in Canada, while size plays no significant role.

Chan (2003) documents a material difference between the prevalence of momentum in firms with public news and those with no news (but similar past returns). The drift in prices, which lasts for up to 12 months, is more pronounced for firms with bad public news, consistent with an underreaction to bad news. The prices of firms with no conspicuous news tend to reverse in the subsequent month, suggesting that the original price change was an overreaction to spurious price movements, possibly caused by positive feedback traders[17]. Pritamani and

[17] The effect may also be caused by bid-ask bounce, transaction costs, short-sale constraints and limits to arbitrage, as drifts are more common among smaller, low-priced, and illiquid loser stocks.

Singal (2001) also show that large price changes coupled with public announcements display momentum, while price changes with no accompanying news do not (and display evidence of reversal). Momentum in returns is more pronounced when news is related to earnings or analyst recommendations.

The results are entirely consistent with the models of Hong and Stein (1999) and Daniel *et al.* (1998), which predict underreaction to public information and overreaction to private information. In a similar vein, Cohen *et al.* (2002) show that expected cash flow changes account for momentum. Cohen *et al.* (2002) show that institutional investors trade with, and profit from, individual investors who underreact to cash-flow driven price rises and overreact to spurious price movements (i.e. those unrelated to cash flows).

Jackson and Johnson (2006) show that momentum and PEAD are manifestations of the same underlying phenomena. Both anomalies are caused by changes in expected earnings (or growth thereof) and momentum only exists because investors attempt to predict future changes in earnings. PEAD occurs not because of delayed reaction to reported earnings but because of the manner in which reported earnings alter expectations of future earnings. Expected earnings (proxied by analysts' forecasts) are shown to underreact to prices and corporate actions, thereby leading to continuation. Momentum is merely the aggregate effect of PEAD across time and various news events (both observable and less conspicuous).

Battalio and Mendenhall (2005) show that small investors base their earnings expectations on simplistic random walk models, which are less accurate than analysts' forecasts. Such traders thus underreact to the information contained in current earnings, consistent with the hypothesis of Bernard and Thomas (1989). Investors who initiate large trades incorporate analysts' forecast errors into their expectations and respond in a more timely and complete fashion.

Continuation can also result from the delayed reaction of investors to news. Ho and Michaely (1988) and Huberman and Regev (2001) find that investors sometimes react to the republication of information. It may appear to the econometrician that the investor is following a positive feedback trading strategy when in fact they are responding to news in a delayed fashion. If the price-sensitive information contained in the news has already been priced into the share then this delayed reaction could cause continuation followed by reversal.

Evidence of continuation followed by reversal is consistent with the underreaction hypothesis. Alwathaninani (2012) documents significant evidence of momentum (year 1) followed by reversal (years 2-5) that is robust to the four-factor model and consistent with the behavioural models of Barberis *et al*. (1998) and Daniel *et al*. (1998). Similarly, Schneider and Gaunt (2012) document momentum followed by reversals in Australia.

Hong *et al*. (2007) find that industry returns predict individual stock returns and such predictability is linked to the ability of an industry to forecast various indicators of economic activity. Hong *et al*. (2007) conclude that this suggests that stocks markets react in a delayed fashion to the information contained in industry returns i.e. gradual diffusion of information.

Zhang (2008) finds that stock prices react slowly to news and momentum returns are higher when there is greater information uncertainty surrounding an announcement. Zhang (2008) uses firm size, firm age, analyst coverage, dispersion in analyst earnings forecasts, stock volatility, and cash flow volatility to proxy for information uncertainty. Mikhail *et al*. (2003) find that PEAD is lower for firms that are followed by more experienced analysts. Furthermore, Hvidkjaer (2006) uses transactions data to show that small investors in the US react in a sluggish manner to past returns, thereby potentially causing momentum.

Berggrun and Rausch (2011) find that momentum returns have disappeared in Columbia and attribute this to greater information diffusion. Barros and Haas (2008) reach a similar conclusion when evaluating 15 emerging markets. This suggests that the paucity of evidence for momentum returns in Asian markets may be driven by the later sample period employed in many of such studies.

Hirshleifer *et al.* (2009) show that underreaction is caused by investors' limited attention. They find that the immediate price and volume reaction to earnings surprises are much weaker, and post-announcement drifts are much stronger, when there is a significant number of other firms announcing earnings on the same day. Peng and Xiong (2006) show that limited investor attention leads to category-learning behavior, whereby investors tend to process more market-wide information than firm-specific information.

2.6.4 Conservatism bias

Underreaction may occur due to investors' conservatism. Edwards (1968, cited in Doukas and McKnight, 2005) identified the phenomenon of conservatism, whereby investors do not update their beliefs adequately in terms of strength and weight of new information in violation to Bayes' rule. As J.K. Galbraith notes, "faced with the choice between changing one's mind and proving that there is no need to do so, almost everyone gets busy on the proof". Barberis *et al*. (1998) argue that momentum results from conservatism bias combined with the 'representative heuristic', as described by Tversky and Kahneman (1974). Representativenss means that investors ignore the laws of probability and behave as if recent events are typical of the return-generating process.

Barberis *et al*. (1998) argue that frequency of over- or underreaction depends on investors' beliefs about mean reversion. If investors feel that share prices are mean-reverting and a new signal suggests that they are not, investors react to this information with conservatism (believing that at least part of the effect of the information will be reversed in the next period) and thus underreaction will result. Doukas and McKnight (2005) find that momentum can be explained by conservatism (and gradual information diffusion), as investors do not place adequate emphasis on the statistical weight of new information.

2.6.5 Anchoring bias

Judgements are comparative in nature and even when subjects have all the relevant information at hand they tend to use a benchmark for comparison purposes (anchoring). Mussweiler and Schneller (2003) argue that this is all the more prevalent in investing decisions since the information is more difficult to obtain or process.

Mussweiler and Schneller (2003) show that participants provide higher (lower) target prices when basing their estimates on charts with clear highs (lows) at their mid-point. This suggests that investors tend to go against the trend in that they expect share prices to revert towards the recent high or low. However, if the recent high or low is at the end of the series then investors expect share prices to continue and thus adopt a strength rule strategy. This is consistent with the finding of De Bondt (1993) that investors tend to extrapolate current trends into the future. Kaustia *et al.* (2008) show that financial market professionals exhibit a strong anchoring effect, which does not tend to dissipate with experience.

George and Hwang (2004) find that a large proportion of momentum profits are explained by the 52-week high price. The authors find that returns generated by sorting based on 52-week highs are approximately twice as large as those based on past returns to individual stocks or industries. Furthermore, returns using the 52-week high price do not tend to reverse in the long run, suggesting that short-term momentum and long-term reversals are largely separate phenomena. However, Du (2008) finds that the 52-week high momentum profits reverse in the long run using 18 stock market indices suggesting that the two phenomena are strongly linked.

George and Hwang (2004) posit that investors use the 52-week high as a reference point and are reluctant to push shares over that high when new positive information becomes available. This anchor-and-adjust bias causes a delayed reaction (continuation) when the information prevails and the price pushes through the barrier of its previous high. Similarly, investors are disinclined to sell when current prices are significantly distanced from their 52-week high. The authors argue that underreaction to news peaks at or near 52-week highs. Marshall and Cahan (2005) present evidence of significant abnormal returns to the 52-week high momentum strategy in the Australian market and conclude that such returns are robust to adjustments for size, liquidity, and risk.

Using a sample of 20 major stock markets, Liu *et al.* (2011) show that the 52-week high momentum effect is robust in international markets. Profits to such a positive feedback trading strategy are positive in 18 of 20 markets analysed, ten of which are statistically significant. Liu *et al.* (2011) show that the 52-week high returns exist independently from the individual and industry momentum returns of Jegadeesh and Titman (1993) and Moskowitz and Grinblatt (1999), respectively. Consistent with George and Hwang (2004), Liu *et al.* (2011) find that momentum returns do not reverse in the longer term.

Li and Yu (2012) conjecture that overreaction to bad news will be at its peak when the current price is far from its historical high, as at this level it is likely that there has been a series of bad news and traders overreact to prolonged news. As expected, Li and Yu (2012) find that nearness to the Dow 52-week high positively predicts future aggregate market returns, while proximity to the historical high negatively predicts future market returns. In other words, nearness to 52-week (all-time) highs is a proxy for underreaction (overreaction).

Li and Yu (2012) also show that the value premium is much weaker among firms for which overreaction is less likely, that is, for which the 52-week high equals the historical high. Furthermore, momentum is about three times stronger for stocks for which the 52-week high equals the historical high. In summary, they provide strong evidence that behavioral-bias-motivated variables have strong power to forecast future aggregate market returns.

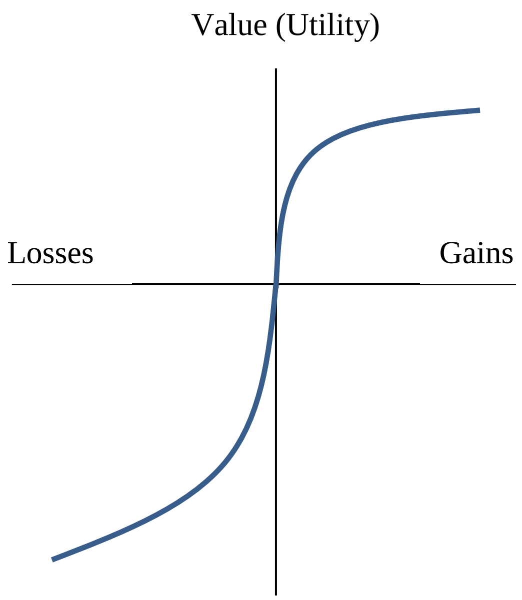
2.6.6 Prospect theory and the disposition effect

Another possible explanation of the momentum effect is derived from prospect theory (Kahneman and Tversky, 1979) and mental accounting (Thaler, 1980). Prospect theory is an alternative to standard expected utility theory, which evaluates people's choices in terms of gains and losses rather than final outcomes (levels of wealth). Mental accounting refers to the ways in which people aggregate and evaluate choices over time, i.e. how they are framed.

Using experimental choices, Kahneman and Tversky (1979) find that people tend to overweight outcomes that are considered certain over probable ones – the *certainty effect.* Subjects are found to be risk averse in the domain of gains and risk seeking in the domain of losses. This is because in the domain of gains the certainty effect leads subjects to a risk-averse preference for a sure gain over a larger but merely probable gain. Conversely, in the domain of losses the certainty effect leads to a risk-seeking preference for a probable rather than a lower certain loss. Thus, the utility function is concave for gains, convex for losses, and is steeper for losses than for gains, as illustrated in figure 2.2.

Figure 2.2

Prospect theory value function



Source: Kahneman and Tversky (1979)

A combination of prospect theory and mental accounting generates a *disposition effect*, a term introduced by Shefrin and Statman (1985). This is the tendency for investors to sell winners too quickly and hold on to losers for too long. Odean (1998a) finds that investors prefer to sell winners than losers. Such behaviour does not seem consistent with a desire to rebalance portfolios, avoid high trading costs and does not seem to lead to superior subsequent performance (the winners that are sold outperform the losers that are retained in subsequent periods).

The disposition effect may appear consistent with contrarian investment strategies. Indeed, Andreassen (1987) finds that subjects behave as if expecting short-term mean reversion when buying and selling stocks in an experimental setting. However, it could also explain return continuation. If price goes up but is then stabilised by the disposition effect, more investors may continue to buy the stock in the belief that the disposition effect selling has caused the price to fall short of its fundamental value. Thus, there will be continuation (positive autocorrelation) of returns. Barber and Odean (1999) infer that investors' reluctance to sell losing stocks leads to underreaction to news as bad news is slowly incorporated into share prices.

Grinblatt and Han (2005) formally examine the link between prospect theory, mental accounting, and momentum. The authors find that a proxy for aggregate unrealised capital gains is the key driver of momentum returns. Frazzini (2006) shows that the disposition effect can lead to underreaction to news. Bad news travels particularly slowly for stocks trading at large capital losses as investors are reluctant to realise their losses. In contrast to the assertion that investors sell winners too quickly, Frazzini (2006) finds that goods news also travels slowly among stocks trading at large capital gains. Phua *et al.* (2010) test behavioural theories relating to momentum in Australia and conclude that the anomalous returns are more consistent with the disposition effect than the overreaction effect.

Muga and Santamaria (2009) argue that the disposition effect may lead to momentum in both up and down market states, contradicting the findings of Cooper *et al.* (2004), as outlined in section 2.5. The authors stress the importance of the magnitude of unrealised gains and losses relative to the reference price. The case for an important role for the disposition effect is enhanced by the finding that reference price portfolios predict returns as well as past returns and the 52-week high loser portfolio has greater predictive power in down markets than past returns. Furthermore, momentum returns following up markets reverse suggesting an overreaction. However, there is no such reversal following down markets, which suggests that the disposition effect leads to underreaction (as argued by Grinblatt and Han, 2005).

2.6.7 Myopic loss aversion

The combination of loss-aversion and mental accounting is central to the concept of myopic loss aversion (MLA), as outlined by Benartzi and Thaler (1995). MLA refers to a situation where an investor evaluates gains and losses in the short run, rather than aggregating returns into a lifetime portfolio. As Kahneman and Tversky (1979, p.287) state "a person who has not made peace with his losses is likely to accept gambles that would be unacceptable to him otherwise".

Barber and Odean (1999) assert that loss aversion drives the disposition effect. In examining trades randomly selected from 10,000 brokerage accounts the authors discount alternative explanations such as taxation, rebalancing, and transaction cost considerations or a belief in mean reversion.

Researchers such as Thaler *et al*. (1997), Gneezy and Potters (1997) and Gneezy *et al*. (2003) find evidence of MLA, albeit predominantly with inexperienced traders (such as students). However, MLA is not exclusive to such traders. Haigh and List (2005) find that professional traders (from the Chicago Board of Exchange) exhibit behaviour consistent with MLA to a greater extent than students. Shavit *et al.* (2010) provide physical evidence of the importance of mental accounting and loss aversion in an experimental setting using eye tracking techniques. Subjects spend more time looking at the final value of an asset than the portfolio's final value. Furthermore, subjects tend to spend more time looking at changes in an asset's value than its final value and nominal changes receive more attention than percentage changes.

Menkhoff and Schmeling (2006) show that momentum returns can survive the process of arbitrage because MLA requires substantial returns even with modest transaction costs. Momentum strategies only become worthwhile for evaluation periods of one year and beyond. This may explain why momentum persists for periods of approximately one year but is practically non-existent for longer periods in existing momentum studies.

2.6.8 Overconfidence

De Bondt and Thaler (1995, cited in Daniel and Titman 1999, p.28) state that "overconfidence is perhaps the most robust finding in psychology of judgement". Studies on the overconfidence of professionals can be traced back to Oskamp (1965), who examines the overconfidence biases of clinical psychologists. Overconfident security analysts and economic forecasters were first studied by Ahlers and Lakonishok (1983) and Froot and Frankel (1989). Overconfidence can lead to PEAD or momentum as investors and analysts fail to update their beliefs adequately in the face of earnings surprises (or other information that contradicts their opinions), thereby causing prices to drift.

Benos (1998) and Hirshleifer and Luo (2001) argue that overconfident traders can earn higher profits by bidding more aggressively than rational traders; thereby causing momentum in returns by pushing prices beyond their fundamental values. This is consistent with the finding that overconfidence increases with experience (Van de Venter and Michayluk, 2008). A further theoretical link between overconfidence and momentum is provided by Odean (1998a), who finds that market returns may display positive serial correlation when overconfident traders underreact to information from rational traders.

Barber and Odean (1999) find that overconfident investors sell winners prematurely, hold losers for too long, trade more frequently, and make bigger losses. Overconfidence leads investors to believe that they have greater information or ability than is actually the case. Barber and Odean (1999) show that the stocks that traders buy underperform those that they sell, even when transaction costs are ignored.

De Bondt (1998) shows that surveyed investors are overconfident about the shares that they bought but not overconfident about the market as a whole. Furthermore, investors provide overly narrow confidence intervals on the variability of security prices and underestimate the covariation in returns between their own portfolio and the market index. This shows that investors are susceptible to all four sources of overconfidence, i.e. unrealistic optimism, illusion of control, miscalibration, and better-than-average effect.

Daniel *et al*. (1998) argue that momentum may be caused by continuing overreaction by overconfident traders, reinforced by self-attribution bias rather than by underreaction[18]. This arises because overconfident investors put too much weight on their own private information and underweight public information. Thus, investors overreact to private information and underreact to public information. However, because of self-attribution bias investors adjust slowly when public information contradicts their private beliefs and continue to overreact if the information confirms their beliefs. Thus, there is an on-going overreaction with share prices moving away from their fundamental value.

In a theoretical setting, Odean (1998b) shows that the presence of a many overconfident traders leads to markets underreacting to the information of rational traders. Odean (1998b) shows that markets underreact to abstract, statistical, and highly relevant information, and overreact to salient, anecdotal, and less relevant information. Daniel and Titman (1999) also show that overconfidence can generate momentum in returns.

Chui *et al.* (2010) find that momentum returns are positively correlated to an individualism index, as developed by Hofstede (2001 cited in Chui *et al.*, 2010), which measures overconfidence and biased self-attribution. According to Chui *et al.* (2010), it is thus cultural differences that explain the varying momentum returns across countries. In nations with low levels of individualism (such as Asian nations), investors are less likely to act like the overconfident/self-attribution biased investors that can cause momentum as described in this section.

Scott *et al.* (1999) argue that investor underreaction is caused by overconfidence that leads investors to overweight their own valuation of a share and underweight news that contradicts their views. Scott *et al.* (2003) show that investors underreact to analysts' forecast revisions for high-growth stocks only. The authors argue that news affects the share price of such companies as there is greater uncertainty surrounding their prospects. This is of particular

[18] Self-attribution bias, as identified by Bem (1965), refers to the tendency for people to attribute success to their own abilities and failure to external factors (such as bad luck) or to place too much significance on signals that confirm their beliefs and ignore signals that contradict them.

relevance to momentum strategies as companies with rapid growth are more likely to be classified as winners.

Cooper *et al*. (2004) explain how the models of Daniel *et al.* (1998) and Barberis *et al.* (1998) predict that momentum returns should be larger *following* up markets due to the increased overconfidence and reduced risk aversion that accompany greater wealth. In both models, a correction of this mispricing should manifest itself in long-term reversals. Therefore, momentum and reversals should be larger following bull markets. The authors find that these behavioural models cannot fully explain the momentum and reversal anomalies in the US, as short-term continuation does not tend to precede long-run reversals following market downturns. Momentum profits exclusively follow bull markets but reversals occur after both market types and are more significant following down markets. Thus, reversals are not solely corrections of previous mispricings due to momentum.

2.7 Breakdown of returns

Considerable research has examined whether the momentum effect is present at the firm-, industry-, or country-level in order to gain an insight into the causes of return continuation. The firm-specific attributes of momentum stocks such as size, book-to-market ratios, and value versus growth stocks are also of interest.

2.7.1 Industry and style momentum

Individuals have a tendency to group similar items together in order to simplify problems of choice and economically evaluate large amounts of information (Rosch and Lloyd 1978 cited in Barberis and Shleifer, 2003). Investors tend to classify stocks as being small-cap/large-cap, value/growth, etc. and investing on this basis is referred to as ‘style investing’ (Bernstein, 1995 cited in Barberis and Shleifer, 2003). Sharpe (1992) shows that 97% of a leading fund’s superior performance in the 1980s is attributable to correct investment style allocation rather than superior stock picking.

Barberis and Shleifer (2003) postulate that style-based momentum strategies are more profitable than their traditional individual-firm counterparts. Chan *et al*. (2002) find that value/growth and size are important components of style. Different styles are more useful in different periods – no single style dominates. Style momentum strategies involve buying stocks that are currently in favour and selling those out of favour.

Chen and De Bondt (2004) argue that pressure from clients may force fund managers to pursue such a strategy despite their own personal beliefs. If a sufficient number of fund managers invest in style momentum then its success can become a self-fulfilling prophecy. If this is the case the strategy should succeed only in the short- to medium-term and be followed by a reversal in the long-run[19]. Chen and De Bondt (2004) find that stocks with favourable style characteristics outperform those with unfavourable style characteristics by 20 to 60 basis points per month and assert that style momentum is distinct from price and industry momentum.

Investing in particular industries is another popular method of grouping stocks. Moskowitz and Grinblatt (1999) find that industry momentum accounts for the vast majority of individual stock momentum. The authors find that the profitability of industry momentum strategies are significant and remain unaffected after controlling for size, book-to-market equity, individual stock momentum, the cross-sectional dispersion in mean returns, and potential microstructure influences. Furthermore, contrary to the findings of other studies, the strategy seems to be profitable when used on large, liquid stocks and abnormal returns are largely accounted for by the buy side profits. The optimum period for investing in industry momentum strategies is the short term (one-month horizon). Profits tend to fall after the 12-month horizon and reversal is often found, as is the case with individual momentum strategies.

It should not be thought that the argument that industry momentum is the main cause of the profitability of a strength rule is in conflict with the behavioural explanations. Moskowitz and Grinblatt (1999) argue that the two explanations are not mutually exclusive. If an

[19] Teo and Woo (2001) provide evidence of style-related return reversals.

investor is to profit from momentum they will attempt to set up an arbitrage position by longing past winners and shorting past losers (weighted so that it has a similar factor beta configuration as the winner portfolio). They will attempt to diversify away firm-specific risk. However, firms within an industry tend to be more highly correlated than stocks across industries. Therefore, momentum strategies will not be arbitrage opportunities as firm-specific risk cannot be diversified away. This expounds why apparent arbitrage opportunities persist.

Scowcroft and Sefton (2005) also show that industry momentum is the main driver of price momentum in the MSCI World Index of developed countries; while O'Neal (2000) presents evidence of significant abnormal returns to industry momentum strategies in the US. Nijman *et al*. (2004) find that the momentum strategy for large European stock generates an excess return of approximately 12% per annum. Individual stocks account for 60% of the total momentum effect, with industries and countries only accounting for 30% and 10%, respectively. The results are robust to the inclusion of value and size effects. Grundy and Martin (2001) find that momentum returns cannot be fully explained by industry risk or cross-sectional differences in returns.

Pan *et al*. (2004) find that the industry momentum effect is mainly attributable to the own-correlation in industry returns as opposed to return cross-autocorrelations (as argued by Lo and MacKinlay 1990a) or cross-sectional differences in mean returns (as argued by Conrad and Kaul, 1998). This is consistent with the behavioural models of Hong and Stein (1999), Barberis *et al*. (1998), and Daniel *et al*. (1998). This finding also supports Moskowitz and Grinblatt's (1999) assertion that industry momentum is driven by serial correlation in industry returns. Lewellen (2002) and Wu and Wang (2005) find that the industry momentum profits produced by portfolios sorted by size and/or book-to-market ratio can be explained by the Fama-French three-factor model.

Du (2009) also reports evidence of short-run momentum in US industry portfolio returns and finds that serial correlations are the main driver of such anomalous returns when long-run momentum is mainly due to cross-serial correlations. Muga and Santamaria (2007a) find that it is solely new economy stocks that exhibit momentum in Spain, while Aarts and Lehnert (2005) find that style momentum strategies fail to outperform traditional momentum strategies in the UK.

2.7.2 Firm-specific attributes

The firm-specific characteristics of stocks that comprise the winner portfolio often systematically differ from those of the loser portfolio on dimensions other than past returns. Sagi and Seasholes (2007) find that momentum strategies based on firm-specific attributes such as high revenue growth, low costs, and valuable growth options outperform traditional strength rule strategies by approximately 5% per annum. Firms with high revenue volatility (a proxy for high information uncertainty) earn momentum profits 6-14 percentage points higher than those with low revenue-volatility. Momentum profits are 2-9 percentage points higher for firms with low costs of sales; are higher in up markets, and are approximately 10 percentage points higher for high book-to-market firms.

Lee and Swaminathan (2000) find that past trading volume is a key predictor of momentum returns. They find that firms with high past turnover earn lower future returns and have more negative earnings surprises over the next eight quarters. The opposite is the case for low turnover stocks. High (low) volume stocks are associated with glamour (value) characteristics and high-turnover stocks experience a subsequent reversal quicker than low-turnover stocks. The authors find that a strategy of buying past winners with low trading volume and selling past losers with high trading volume outperforms standard momentum strategies by 2–7 percentage points per annum.

Arena *et al.* (2008) show that momentum returns are higher for stocks (especially losers) with high idiosyncratic volatility. The authors conclude that this implies that momentum is caused by underreaction to firm-specific news and idiosyncratic volatility represents a limit to arbitrage as suggested by Shleifer and Vishny (1997). Arena *et al.* (2008) also document a positive relationship between aggregate idiosyncratic volatility and momentum returns, which may explain the persistence of the anomaly as such volatility has increased over time.

Lo and MacKinlay (1988) present evidence of significant positive serial correlation in weekly and monthly returns. Although the effect is more pronounced for smaller stocks, the authors show that it is not solely attributable to infrequent trading. Similarly, Glaser and Weber (2003) find that momentum strategies on the German market are more profitable among high-turnover stocks.

Hong *et al*. (2000) find that there are no significant momentum profits when very small stocks are excluded. Rouwenhorst (1999) finds that momentum in emerging markets is mainly driven by small stocks and value stocks. However, Rouwenhorst (1999) finds that there is no correlation between expected returns and turnover in emerging markets and Phua *et al.* (2010) show that momentum returns in Australia are more significant for larger firms. Furthermore, Fama and French (2008, p.1653) show that the anomaly is pervasive, with abnormal returns present for all size groups.

Eisdorfer (2008) finds that approximately 40% of momentum returns are accounted for by delisted firms. It is primarily bankrupt firms that contribute to this delisting profit, with merged firms having only a minimal effect. Furthermore, *ex-ante* momentum returns can be increased by focussing on firms with a higher probability of bankruptcy and excluding firms that are likely to merge. Notably, Eisdorfer (2008) shows that the momentum returns are almost exclusively accounted for by the delisting returns. This suggests that a significant proportion of momentum profits do not accrue during the normal day-to-day trading of firms but occur in the final throes of the delisting process. The limitations around short selling in the run up to a delisting may make it impractical or impossible for an investor to harvest any momentum returns.

Avramov *et al*. (2007) highlight the link between momentum profits and credit ratings. They find that firms with low bond-ratings exhibit significant return momentum, while momentum is absent for high-grade firms. The low-grade firms account for less than 4% of the market capitalisation and excluding this small group of firms renders momentum profits insignificant. Avramov *et al*. (2007) also find that firms with high bankruptcy risk exhibit strong momentum, while Agarwal and Taffler (2008) conclude that momentum in the UK is driven by underreaction to financial distress (bankruptcy) risk.

2.7.3 Country vs. firm level

The majority of momentum studies examine returns at the firm level. More recently, research has examined whether there is momentum in stock market indices. Chan *et al*. (2000) find evidence of a six-month momentum effect at the country index level and find that momentum profits are positively correlated with past trading volume.

Shen *et al*. (2005) test the momentum strategy at the country level on both growth and value indices. Shen *et al*. (2005) put forward two reasons as to why momentum strategies may work when used in conjunction with growth stocks. First, analysts tend to underestimate earnings growth for past winners (see Chan *et al*., 1996). Furthermore, Skinner and Sloan (2002) show that growth stocks tend to be more sensitive to earnings surprises (thus positive earnings surprises will also have a greater impact on winner stocks that are also growth stocks). Second, there is a greater level of uncertainty surrounding the valuation of growth stocks. Furthermore, Miller (1977) argues that in the absence of total access to short selling, the most optimistic investors will have a disproportionate impact on share prices and thus the greater the uncertainty about a stock's value, the more it will be overvalued.

Shen *et al*. (2005) find that momentum profits are concentrated in growth industries and there is evidence of short-term overreaction that is subsequently corrected. The return pattern found by Shen *et al*. (2005) is similar to those of Jegadeesh and Titman (1993) in that the momentum strategy is profitable six-nine months into the test period, after which they become negative (and thus the contrarian investment strategy is profitable for such a period) until the end of the 36-month extended test period. In fact, all of the strategies regardless of the formation period earn negative profits in every six-month period after the first year.

The above findings (continuation followed by reversal) are consistent with many studies, such as Conrad and Kaul (1998) whereby the contrarian investment strategy is profitable in the short-term (1-3 months), and the long-term (2-5 years), whereas the momentum strategy is profitable over the medium-term (3-12 months). If momentum profits were mainly attributable to cross-sectional differences in mean returns (as argued by Conrad and Kaul, 1998) then past winners should continue to outperform past losers indefinitely. Since this is not the case it cannot fully explain the persistence of the continuation phenomenon. Bhojraj and Swaminathan (2006), Asness *et al.* (1997) and Chan *et al.* (2000) also document evidence of momentum using data from stock market indices.

Menzly and Ozbas (2006) present evidence of cross-industry momentum as industries related to each other through the supply chain exhibit significant momentum. A strategy of buying (selling) firms whose upstream counterparts experienced large positive (negative) returns yields excess abnormal returns of 6% per annum.

2.7.4 Seasonality, tax loss-selling, and window dressing

It may be expected that a momentum strategy would perform poorly in January, as the tax-loss selling and window-dressing hypotheses imply that investors sell past losers and small stocks at the end of the tax year and re-purchase them in the following month. Jegadeesh and Titman (1993) confirm this by finding that the momentum strategy registers mean losses of 7% in January and positive returns in all other months. Similarly, Grundy and Martin (2001) report a mean loss to the strategy of 5.85% in January, with only 15 out of the 69 periods registering positive January returns[20].

Jegadeesh and Titman (1993) and Grinblatt and Moskowitz (2004) show that momentum profits tend to be highest in December. Furthermore, Grinblatt and Moskowitz (2004) show that momentum and seasonal effects tend to be more pronounced for small stocks with high turnover and low institutional ownership. They also show that seasonality in momentum

[20] Grundy and Martin (2001) report a mean return to non-January months of 1.01%.

profits is only evident in high-tax years. Taken together, this seems to support the tax-loss selling hypothesis as an explanation for the January effect[21].

In light of these findings, a momentum strategy that excludes January may be superior to one which holds stock for the full year. Sias (2007) finds that this is the case for US stocks and also concludes that momentum strategies tend to be considerably more effective for quarter-ending months, especially December, suggesting that window dressing or tax-loss selling is prevalent. Sias (2007) further recommends focussing on stocks that have high levels of institutional trading. Fu and Wood (2010) show that momentum returns in Taiwan are confined to months following the deadline for annual statements, suggesting that momentum returns are linked to earnings surprises.

2.8 The role of brokers/analysts/investment houses

In addition to being overconfident the behaviour of brokers/analysts can explain the momentum anomaly in three ways. First, brokers' have conflicts of interest and are thus more likely to issue buy recommendations (Michaely and Womack, 2004) and are slow to revise their earnings forecasts downwards (Erturk, 2006). Second, herding behaviour can cause stocks to deviate from their fundamental value (Caparrelli *et al*., 2004) and finally, analysts often follow momentum strategies and are prone to underreaction (Bhaskar and Morris, 1984).

If the majority of shares are held by institutions, any positive feedback trading by such institutions may directly induce momentum in returns. Similarly, the recommendations of brokers may indirectly cause positive serial correlation in returns as brokers tend to recommend stocks with recent positive performance and such recommendations are taken at face value by investors; thereby materially impacting share prices. The impact of momentum trading by these key financial participants is magnified by their observed tendency to herd. These issues are examined in greater detail in chapter four.

[21] For evidence of these explanations of the January effect see, *inter alios*, Sias and Starks (1997); Gultekin and Gultekin (1983); and Reinganum (1983).

2.9 Summary and conclusions

This chapter synthesised the evidence relating to the momentum anomaly and discussed the theories that have been postulated to explain the emergence and persistence of the anomaly. Momentum returns were categorised on the basis of several firm-specific characteristics such as size, book-to-market, trading volume, costs, revenue volatility and a key distinction was made between the evidence pertaining to value and growth stocks and country and industry, as opposed to, firm-level momentum.

Overall, the chapter presented convincing evidence of the existence of a strong and pervasive momentum effect across geographical and temporal dimensions. It was also shown that there is a dearth of evidence pertaining to the four markets that are the focus of this study. While the existence of return continuation is widely accepted, one can conclude that the cause of such an apparent violation of the EMH is an open issue.

Rational explanations, such as transaction costs, risk, model mis-specification and short-selling constraints, were shown to only partially account for the vast body of evidence in favour of significant momentum returns. The evidence suggests that brokers play a significant role in explaining momentum returns, while behavioural explanations continue to gain acceptance. The behavioural and brokerage views should not be seen as rival theories in accounting for the momentum anomaly but are very much interrelated areas that warrant further attention and this will be given in chapter four.

Chapter Three

The Winner-Loser Anomaly

3.1 Introduction

The winner-loser anomaly remains one of the most puzzling anomalies in finance. The existence of return reversals is axiomatic; however, the cause of such negative serial correlation in returns is considerably more contentious. Significant evidence of return reversals persists in many capital markets despite relentless attacks from proponents of the EMH. This chapter examines the evidence relating to the anomaly and discusses the causes that have been postulated to elucidate its persistence. Given the inter-related nature of the momentum and reversal anomalies, it is natural that many of the causes of return reversals are similar to those discussed in the previous chapter. This chapter focuses on additional explanations and evidence specific to the winner-loser anomaly in order to avoid repetition. It also emphasises the seminal distincion between short- and long-term return reversals.

The remainder of this chapter is organised as follows. Section 3.2 provides a backgroud to the winner-loser effect, with particular emphasis on the early evidence adduced in favour of the anomaly. Additional evidence is presented in section 3.3, while section 3.4 discusses the evidence relating to short-term return reversals. Section 3.4 introduces the causes that have been postulated to explain the putative anomaly; the behavioural and rational explanations are discussed in sections 3.6 and 3.7, respectively. The potentially important contribution of brokers to the winner-loser effect is highlighted in section 3.8 and section 3.9 concludes.

3.2 The winner-loser anomaly

The 'winner-loser' effect is an anomaly that seems to point to the rejection of market efficiency, highlighting a potential trading strategy with which it may be possible to make abnormal profits on a systematic basis. The anomaly refers to the phenomenon whereby stocks that have performed relatively poorly (losers) over a specified period tend to perform relatively well in the subsequent period and *vice versa* for winners. Thus, there is a reversal of fortunes with stock prices displaying negative serial correlation and being mean reverting in nature. Work on the winner-loser anomaly is motivated by Graham (1949 cited in De Bondt and Thaler, 1985), who advocated the purchase of stocks whose prices appeared low relative to their fundamental value.

A contrarian investment strategy attempts to profit from the vicissitudes of the market by buying (long) stocks that have been losers and selling (short) those that have been winners. It is based on the belief that stock prices revert to their means ('what goes up, must come down' and *vice versa*) and is similar to a filter rule. The holding period for a contrarian strategy is usually longer than that implied by a filter rule and thus transaction costs are less prohibitive than with the frequent buying and selling involved in a filter rule. Empirical support for the strategy suggests that investors can make potentially profitable use out of past price information and thus poses a significant challenge to the EMH.

The phrase 'contrarian strategy' generally refers to the purchase of past losers and the simultaneous short-sale of past winners. However, past stock price performance is not the only measure of firm value/performance that investors can use to select stocks for a contrarian strategy. 'Value' strategies use variables such as book value, cash flow, earnings, and dividends to form portfolios that are long in value stocks and short in growth stocks. Although most of the evidence in this chapter refers to the contrarian strategies based on price, the term is also used to refer to value strategies. There is considerable overlap beyween the two concepts as stocks that have performed poorly over a specified period are, *ceteris paribus*, also likely to have lower measures of value such as size and earnings.

In two papers central to the anomaly, De Bondt and Thaler (1985 and 1987) argue that investors tend to overreact to moving share prices. Accordingly, stocks that have fallen most in price during the previous three to five years ('losers') will tend to yield excess returns over the following three to five years and *vice versa* for stocks performing well over the same period ('winners'). De Bondt and Thaler (1985) use monthly data from the New York Stock Exchange for the period 1926-1982 and find that loser portfolio outperforms the market by an average of 19.6% in the 16 non-overlapping three-year test periods. The winner portfolio earns approximately 5% less than the market, giving a difference in cumulative average residuals between the extreme portfolios (and thus a profit form a contrarian investment strategy) of 24.6%.

The overreaction phenomenon primarily occurs during the second and third year of the test period, with a small reversal in the first year. This is partly consistent with the phenomenon of 'continuation followed by reversal'. Furthermore, the overreaction effect is asymmetric, being much larger for losers than for winners. The excess returns are predominantly realised in January; however, the authors show that the overreaction effect is not merely a manifestation of the January effect but is an important anomaly in its own right. The results of De Bondt and Thaler (1985) represent a *prima facie* rejection of the EMH.

3.3 Additional evidence of long-run reversals

The findings of De Bondt and Thaler (1985) spawned a plethora of related research, resulting in a burgeoning body of evidence consistent with return reversals across temporal and geographical partitions, using a varierty of methodoglical approaches. This section outlines a cross-section of the key evidence adduced in favour of long-term return reversals. The equivalent evidence in favour of short-term reversals is examined in the subsequent section.

Richards (1997) finds that a contrarian investment strategy executed on national indices yields average excess abnormal returns of more than 6%, with such returns tending to be larger on smaller markets[22]. Mun *et al.* (2000) document significant contrarian returns in the US and Canada, while Baytas and Cakici (1999) document large reversals in Canada. Further evidence of significant long-term contrarian returns in the US market is documented by, *inter alios*, Balvers and Wu (2006), Larson and Madura (2003), and Conrad *et al*. (1997).

Mazouz and Li (2007) find economically and statistically significant contrarian returns in the UK, which persist after accounting for seasonality, firm size, and time-varying risk. Significant long-term return reversals are also documented for the UK by Dissanaike (2002), Campbell and Limmack (1997), Capstaff *et al*. (1995), and Power *et al.* (1991).

[22] Appendix B details the markets analysed in the multi-country studies outlined in this chapter.

Bird and Whitaker (2003) document evidence of contrarian returns in a number of major European markets. Further evidence of return reversal in European markets is documented for Germany (Schiereck *et al.* 1999; Stock, 1990), France (Bacmann and Dubois, 1998; Mai, 1995), Spain (Alonso and Rubio, 1990; Forner and Marhuenda, 2003), Lithuania (Paškevičius and Mickevičiūtė, 2011); by Brouwer *et al.* (1997) for France, Germany, The Netherlands, and the UK, and by Baytas and Cakici (1999) in France, UK, Germany, and Italy.

Schaub *et al*. (2008) examine daily price changes in Korea, Hong Kong and Japan and find that overreaction is limited to past losers. The three indices reversed by 35 to 45% following days of excessive decline. No such reversal was documented for previous winners. Further evidence of significant abnormal contrarian returns in the rest of the world is fournished for Australia (Lo and Coggins, 2006), China (Wang and Xie, 2010; Kang *et al.*, 2002), Japan (McInish *et al*, 2008; Chou *et al.*, 2007), Egypt (Ismail, 2012), India (Locke and Gupta, 2009), Brazil (da Costa, 1994), New Zealand (Chin *et al.*, 2002; Bowman and Iverson, 1998), Malaysia (Lai *et al.*, 2003; Ahmad and Hussain, 2001), Tunisia (Trabelsi, 2010), Hong Kong (Leung and Li, 1998), Turkey (Bildik and Gulay, 2007), and South Africa (Gilbert and Strugnell, 2010; Cubbin *et al.*, 2006; Bailey and Gilbert, 2007). Finally, Barros and Haas (2008) document evidence of significant contrarian returns in a sample of 15 emerging markets.

There is a conspicuous dearth of research on the four markets that are the focus of this thesis. Only one of the studies in appendix B that covers one or more of these markets provides details on the market-specific profitability of the contrarian strategy in any of the four markets. Richards (1997) reports that the contrarian returns in Denmark and Norway are the largest of the 16 markets analysed at 23.5 and 16.8% per annum respectively. Antoniou *et al.* (2006a) report that abnormal returns are insignificant in Greece when time-varying risk measures are employed.

Evidence on the profitability of contrarian investing is not limited to academic circles. Highly successful investors such as Benjamin Graham, Warren Buffett and George Soros attribute their success to value/contrarian strategies. Naturally, the evidence relating to return reversals is not entirely supportive of the anomaly. Subadar and Hossenbaccus (2010) show that there is no significant evidence of return reversals in Mauritius. Value strategies based on size, P/E ratios, and book-to-market ratios are also shown to be of no economic value. Brailsford (1992) and Allen and Prince (1995) find no evidence of the winner-loser anomaly in Australia, while Kyrzanowski and Zhang (1992) reach the same conclusion for Canada. The argument of Fama (1998) regarding data mining, as outlined in chapter two, may explain why the volume of such findings is dwarfed by the more 'splashy' results that give investors hope that large profits can be realised using a relatively straightforward strategy.

3.4 Short-run reversals

The literature often fails to distinguish between short- and long-term return reversals[23]. However, such a distinction is crucial, as the divergent causes that have been postulated to explain the two putative anomalies suggest that they may be largely separate phenomena. This section outlines the evidence adduced in favour of short-run negative serial correlation in returns (contrary to standard theory's assertion that returns follow of a random walk or martingale process).

Significant return reversals have been documented over daily (Bremer and Sweeney, 1988), weekly (Lehmann, 1990), and monthly (Howe, 1986) holding periods. Short-term negative feedback trading is often based on filter rules and can be less profitable in net terms due the increased impact of transaction costs, illiquidity and nonsynchronous trading. However, the short event-window means that return reversals are considerably less compromised by changes in risk levels and lead-lag effects. At first glance, bid-ask spreads would appear to be more relevant for short-term contrarian strategies (as bid-ask bounce is more relevant when prices remain relatively stable). However, the short-term nature of such negative feedback strategies means that such spreads are not cumulated to the same degree as with longer-term equivalents (see Conrad and Kaul, 1993). As Fama (1998, p.283) points out, short event windows allow for cleaner analysis as expected returns are close to zero and thus

[23] Power and Lonie (1993) is a notable exception.

“the model for expected returns does not have a big effect on inferences about abnormal returns”.

Niederhoffer and Osborne (1966) analyse consecutive price movements and report that reversals are three times as likely as continuations. However, after two consecutive price changes in the same direction, further continuation is almost twice as likely as is the case after a reversal. Furthermore, large changes tend to be followed by large changes. Similar evidence is furnished for third- and fourth-order movements. These results are in stark contrast with findings of Cowles and Jones (1937) that continuations are more likely than reversals, as outlined in chapter two. The results of both studies are incongruous with the predictions of the random walk model, as consecutive price changes do not appear to be independent.

Bremer and Sweeney (1988) find that stocks that have fallen in value by more than 10% earn returns of 3.95% over the subsequent five days. The authors only use large firms in order to minimise bid-ask spreads and the small-firm effect. Similar evidence is furnished by Brown and Harlow (1988). Bremer and Sweeney (1991) show that firms with large negative ten-day returns generate positive returns for the subsequent two days. Cox and Peterson (1994) also find reversals in the first three days after extreme price declines, while Larson and Madura (2003) document evidence of significant overreaction to events that cause extreme one-day returns.

Chang *et al.* (1995) report profits to a short-term contrarian strategy in Japan that are robust to risk, firm size, and seasonality, with losers outperforming winners by approximately 2% in the month following portfolio formation. Contrarian returns disappear and become negative over the subsequent months consistent with the stylised pattern of short-term reversal, medium-term momentum and long-term reversal as discussed in chapter two. Iihara *et al.* (2004) also document significant one-month return reversals in Japan that are robust to risk, firm characteristics, and industry classification. Bremer and Hiraki (1999) document similar one-week return reversals in Japan.

Howe (1986) shows that stocks that register extreme declines in the rank week earn significant abnormal returns in the susequent 50-week period, with the majoirty of the abnormal returns concentrated in the first week of the holding period and cumulative returns peaking in week five. Past winners perform poorly over the subsequent 50-week period. Increases in loser betas are negligible, suggesting that overreaction to news, as opposed to risk, is the main driver of return reversal[24].

Lehmann (1990) presents evidence of significant one-week reversals in stock returns that persist after accounting for transaction costs and bid-ask spreads. Lehmann (1990) finds that a one-week contrarian strategy registers a profit 90% of the time and cites investor overreaction or short-run illiquidity as the most plausible explanations for the anomalous returns.

French and Roll (1986) find evidence of significant negative serial correlation in daily returns. Jegadeesh (1990), Rosenberg *et al.* (1985) and Rosenberg and Rudd (1982) confirm these findings using monthly data. Further evidence of the profitability of a short-term negative feedback strategy is documented for the US (Ma *et al.*, 2005; Peterson, 1995; Ketcher and Jordan, 1994; Niederhoffer, 1971), Canada (Assoe and Sy, 2003), the UK (Antoniou *et al.*, 2006b), China (Chen *et al.*, 2012; Kang *et al.*, 2002), Malaysia (Hameed and Ting, 2000) and Australia (Lee *et al.*, 2003).

3.5 Causes of return reversals

There is much disagreement on the causes of the winner-loser anomaly. As with the momentum anomaly discussed in chapter two, there are two distinct schools of thought on the causes of the winner-loser anomaly. The first school argues that anomalous returns are more apparent than real and are compatible with rational explanations. The chief line of attack taken by such defenders of the EMH is that apparently anomalous returns are primarily attributable to model mis-specification; particularly casued by an inadequate quantification of the risks and costs involved in executing a contrarian strategy.

[24] Howe (1986) also shows that the January effect does not explain the anomalous returns.

In stark contrast, advocates of the behavioural paradigm contend that return reversals exist and persist because of investor irrarionality that stems from cognitive biases such as overreaction, overconfidence, noise trading, and herding. Return reversals may also be a manifestation of previously documented anomalies such as January and size effects.[25]

As outlined earlier, some of the following posited causes of return reversals are primarily relvelant for short- or long-term return reversals. For example, bid-ask bounce, lead-lag effects, and transaction costs are more germane for short-term reversals, whereas changes in risk, mean reversion, survivorship bias, and seasonalities are more apposite for negative serial correlation in long-run returns.

3.6 Behavioural biases

All financial transactions emanate from a human decision-making process. Concomitantly, any irrationalities or biases in this process on the part of investors or analysts will manifest themselves in biased share prices, unless such biases are self-cancelling. Mounting evidence from behaviouralists suggests that the evidence of behavioural biases documented in the psychological literature manifests itself in the behaviour of investors and analysts, aggregates to the market level, and has a pervasive and persistent impact on share prices due to limits to arbitrage. The behavioural finance paradigm thus asserts that anomalous returns are caused by systematic psychological biases such as overreaction, overconfidence, noise trading, and herding. A number of these were discussed in chapter two; therefore this section focuses on additional evidence that relates specifically to the winner-loser anomaly.

3.6.1 Overreaction to news

Research in experimental psychology finds that, in violation of Bayes' rule, people overreact to unexpected and dramatic news. The initial study by De Bondt and Thaler (1985) is, they state, an extension into financial circles of this finding. The winner-loser anomaly is often

[25] This explanation does not fit precisely into either the 'rational' or 'behavioural' camp. Although it may suggest that investor overreaction is not the key driver of return predictability, the fact that returns are predictable is nonetheless inconsistent with the idea of an efficient market.

referred to as the 'overreaction effect' - a term borrowed form applied psychology. Previous research primarily focuses on either past prices or past earnings as the most conspicuous forms of ‘news’.

De Bondt and Thaler (1985) argue that overreaction occurs because investors place too much weight on recent news (especially bad news) and prices are thus based too much on current earning power and too little on long-term dividend-paying power (the ‘recency effect’). Investors extrapolate too far into the future on the basis of the present, consistent with the representativeness heuristic (Tversky and Kahneman, 1982, p.31). In other words, naïve investors become excessively pessimistic (optimistic) about the prospects of firms that experienced some form of bad (good) news.

Overreaction is consistent with the so-called ‘bandwagon effect’ and ‘speculative bubbles’. It may also be explained by the ‘hot-hand hypothesis’, which states that traders attempt to unearth trends in stock prices and thereby overestimate the autocorrelation in the series. In an experimental setting, Offerman and Sonnemans (2004) show that overreaction is more consistent with the hot-hand hypothesis than the recency hypothesis.

Realisation of the overreaction effect occurred decades before the ground-breaking studies by De Bondt and Thaler (1985 and 1987). In fact, Keynes (1930, p.360) clearly recognised the bias when he suggested that unexpexted news “will often cause the capital value of the shares to fluctuate by an amount which far exceeds any possible change in its profits due to the event in question”. Keynes (1936) also asserted that:

> … day-to-day fluctuations in the profits of existing investments, which are obviously of an ephemeral and non-significant character, tend to have an altogether excessive, and even an absurd, influence on the market (pp.153-154).

Similarly, Williams (1938, cited in De Bondt and Thaler 1989, p.190) notes that “prices have been based too much on current earning power, too little on long-run dividend paying power.” Dreman (1979 cited in De Bondt and Thaler, 1989) argued that investors systematically overvalue the prospects of the best investments and undervalue those of the worst; thereby extrapolating prices too far into the future causing an overreaction. Ackley (1983, p.5) recognised that "price movements may develop a cumulative momentum in one direction, which can easily overshoot the current long-run equilibrium price." Childs (1984 cited in Power and Lonie 1993, p.330) provides a succinct analogy of the overreaction phenomenon:

> Investors are irrational. They overreact. In boom periods when everyone is optimistic, they act like the guys who are going down to Atlantic City on the bus to beat the gambling houses. And when things turn pessimistic, they act like the guys coming back.

In one of the earliest tests of overreaction, Merrill (1966 cited in Niederhoffer 1971, p.194), tests the market's reaction to five tragic events involving to US presidents and reports that "selling drives prices down to a surprising degree. However, when a day has passed, the market recovers from its panic, and sometimes works upward to a higher level."

Niederhoffer (1971) extends the work of Merrill (1966) by examining the overall stock-market reaction to world events, as measured by content analysis of headlines in the *New York Times*. Niederhoffer (1971) presents evidence of continuation in the first day after bad news headlines, followed by reversals in the following four days[26]. The evidence of continuation need not necessarily imply underreaction, as Niederhoffer (1971) reports that there is a strong tendency for runs of good and bad news on consecutive days. Thus, the market may be reacting rationally to consecutive unique pieces of news. In contrast, good news rarely follows bad news; therefore reversals appear consistent with the correction for an initial overreaction.

Additionally, Niederhoffer (1971) specifically examines the short-term market reaction to bad news relating to presidential illnesses and deaths using a data period that commences with the headline reporting Wilson's dysentery in 1919 and ending with the reporting of

[26] Niederhoffer (1971) also presents evidence of positive serial correlation for large price changes that are unaccompanied by world events but shows that large changes in share prices are considerably more likely following world events than on other days.

Kennedy's assassination in 1963. Niederhoffer (1971) presents evidence of significant declines (averaging 2.8%) on day one of the event window, with reversals consistently registered between days two and five (a combined average of 2.3%). This evidence of market-wide overreaction to dramatic events paved the way for studies of investor reaction to firm-specific news.

Soros (1998) argues that the parabolic price patterns that facilitate profitable contrarian strategies arise due to the virtuous and vicious cycles between price, perception, and fundamentals caused by 'reflexivity'. It is this interactive two-way feedback loop that results in overreaction to news as investors act like positive feedback traders by reacting to the price changes caused by their (or other investors') trades[27]. Eventually, sentiment changes and prices reverse for a sustained period and overreact in the opposite direction. Reflexivity may explain the boom-bust cycle in markets and speculative bubbles, such as the tulip bulb craze of the 1630s. Reversals in the shorter term may be seen as microcosms of such bubbles.

Dreman and Lufkin (2000) conclude that no explanation other than psychological influences can account for the evidence of overreaction that they furnish[28]. The authors also provide evidence that over- and underreaction are possibly part of the same process, as overreaction takes places before portfolio formation, driving prices beyond their fundamental values, after which returns revert towards a more appropriate level. Iihara *et al.* (2004) conclude that short-term contrarian returns in Japan are caused by investor overreaction to news as reversals are more pronounced at the turn of the fiscal year when more news is disclosed.

Dreman and Berry (1995a) show that a correction for previous overreaction occurs when firm-specific news contradicts existing opinions on the companies in question. When good (bad) news arrives for companies that are considered good (bad), investors' perceptions remain unaltered and share prices remain unchanged. However, when contradictory news

[27] Fundamentals alter the thinking of market participants, which in turn affect fundamentals due to the relationship between share price and fundamentals via credit ratings, cost of capital, etc. Reflexivity leads to self-reinforcing effects that cause markets to constantly move away from equilibrium, thereby causing prices to display positive serial correlation followed by a reversal when sentiment changes.
[28] This overreaction is evidenced by large changes in returns that are associated with relatively modest changes in fundamental values.

arrives, i.e. good (bad) news for unfavoured (favoured) companies, investors react strongly due to a change in perception. Consequently, if favoured and unfavoured firms experience the same amount of good and bad news, the net effect will be a markedly superior performance of unfavoured firms.

De Bondt and Thaler (1990) note that laboratory studies in psychology typically rely on non-finance professionals and argue that it is plausible to expect that experienced fianance professionals may not be prone to the same psychological biases. However, the authors show that security analysts are no less prone to overreaction than naïve undergraduates, thereby lending support to behavioural explanations of market anomalies such as the winner-loser effect.

The concept of contrarian investing is inextricably linked to the theory of value investing. According to Graham and Dodd (1934), investors and analysts tend to overemphasise near-term prospects and therefore overprice (underprice) favourable (unfavourable) companies. Stock market participants extrapolate too far into the future, thereby driving stock prices too far in either direction. The reversal of share prices is thus symptomatic of share prices returning closer to fundamental values and is consistent with the mean-reversion hypothesis. Such a reversal should be predictable form past price data alone (thus violating the weak-form EMH). Contrarian strategies based on past stock returns fit into the class of value strategies that advocate buying stocks that are under-priced relative to relative to book value, cash flow, earnings, dividends, sales, or any other measure of a firm's fundamental value.

For example, the price-earnings (P/E) effect by Basu (1977) is consistent with the overreaction effect, as Basu (1977) asserts that the anomaly exists due to temporary excessive pessimism surrounding low-P/E companies. De Bondt and Thaler (1985) argue that overreaction may explain the P/E effect as loser firms are seen to be temporarily undervalued as a result of investor pessimism after bad earnings reports and price falls proportionally more than earnings. When better than expected earnings are announced, investors are surprised and price adjusts upwards. The opposite is the case for winner firms with high price-earnings ratios.

Lakonishok *et al*. (1994) show that returns to value strategies arise because investors naïvely extrapolate past sales or earnings growth. Investors overestimate the future growth of such variables (and underestimate risk) for glamour stocks relative to value stocks. Such systematic bias in expectations persists due to limits to arbitrage and is accentuated by key financial professionals, as outlined by Lakonishok *et al.* (1992), who show that institutional money managers have a tendency to focus on glamour stocks for career prospects, window dressing, and the perceived lower risk of financial distress attached to such firms. Superior returns to value stocks are thus not attributable to risk but are caused by the unwinding of the past biases of naïve investors with extrapolative expectations. Lakonishok *et al*. (1994), La Porta (1996), and La Porta *et al.* (1997) confirm this thesis empirically.

Clayman (1987) shows that firms identified as ‘excellent’ considerably underperform a matched sample of ‘non-excellent’ companies in terms of growth and profitability over the subsequent five years[29]. A portflio of the latter outperformes the former by approximately 11 percentage points per annum, with no apparent increase in risk. Clayman (1987) concludes that the market becomes overly optimistic in its valuation of excellent companies, thereby overestimating their growth, return, and market-to-book values. The opposite is the case for ‘non-excellent’ companies, with significant evidence that accounting measures and returns for both groups revert towards mean values.

Clayman (1987) argues that survivor bias is unlikely to account for the dramatic reversal of fortunes of ‘excellent’ and ‘non-excellent’ companies as mergers and acquisitions were equally as prevalent as bankruptcies in the stock selection period in question. Bannister (1990) shows that the findings of Clayman are exploitable by fund managers. Bannister (1990) includes companies that subsequently dropped out of the S&P 500 and restricts the sample to relatively large companies in order to reduce survivorship and firm size biases. ‘Unexcellent’ companies outperform their more illustrious counterparts by more than 25 percetange points. Furthermore, takeovers were more frequent among unexcellent companies

[29] Excellence is defined according to the sample and criteria used by Peters and Waterman’s (1982) *In Search of Excellence.*

and bankruptcies were extremely rare, and occurred with equal frequency in each group. This suggests that the results are not driven by survivorship bias.

It is often difficult to distinguish between the above causes, i.e. investors' naïve extrapolating of past financial indicators or biased analysts' earnings forecasts. La Porta *et al.* (1997) and Levis and Liodakis (2001) adduce further evidence that the surperiority of value strategies are attributable to erroneous earnings expectations of investors and analysts. The greater frequency of earnings surprises for value stocks shows that analysts extrapolate past performance in a naïve manner that results in an underestimation of the prospects of value firms. La Porta *et al.* (1997) show that the majority of the difference in the returns of value and growth stocks occur arounds earnings annoucements as investors revise their expectations in recognition of their expectation errors.

La Porta (1996) uses analysts' forecasts of growth as a proxy for investors' expectations and finds that expectations are too extreme, thereby supporting the extrapolative expectations hypothesis[30]. La Porta (1996) finds that the returns of a portfolio of stocks with low growth expectations exceed those with high growth forecasts by 20 percentage points. Furthermore, there is no evidence to suggest that such stocks carry additional risk compared to stocks that are more highly regarded.

Bauman *et al.* (1999) examine 21 stock markets and show that value strategies yield excess returns because investors overreact to past growth rates in EPS, as both investors and research analysts assume that past growth rates in EPS will continue into the future. The crucial role played by analysts in explaining anomalous returns is discussed further in chapter four.

Gregory *et al.* (2001) show that value strategies generate significant abnormal returns after accounting for size and risk. Similarly, Gregory *et al.* (2003) show that returns to value strategies are not due to the additional risk of value stocks or macroeconomic risk, i.e. compensation for unobserved risk factors. Badrinath and Kini (2001) and Daniel and Titman

[30] La Porta (1996) acknowledges that analysts' forecasts may be a noisy proxy due to conflicts of interest

(1997) also show that the returns to value strategies are robust to various sophisticated risk-adjustment procedures.

Haugen and Baker (1996) report that a value strategy based on more than 50 security attributes, such as size, book-to-market, and past returns, generates excess returns of approximately 3% per month[31]. Haugen and Baker (1996) show that the strong correlation between firm characteristics and expected returns is common across different time periods and markets and find no evidence that the superior returns are risk related. Further international evidence on the profitability of value strategies is provided by Gilbert and Strugnell (2010); Arshanapalli *et al.* (1998); and Bauman *et al.* (1998).

The above findings relating to value strategies appear to run contrary to efficient market and asset pricing theories, which suggest that the difference in expected returns should be soley determined by risk differentials. If non-risk factors are shown to play an important role then it appears that pricing is biased. However, it can always be argued that the asset pricing model inadequately captures risk or that other biases materially affect the results.

Using more recent data, Hanna and Ready (2005) show that the strategies of Haugen and Baker (1996) fail to outperform the relatively straightforward strategies based on book-to-market and momentum after accounting for transaction costs. The majority of the returns to the value strategy are attributable to momentum returns. Thus, the high turnover and associated trading costs of the strategy mean that it is of no marginal benefit.

Larson and Madura (2003) examine extreme price movements and sub-divide them into 'informed' events, where relevant information is released in the *Wall Street Journal,* and 'uninformed' events, which are not publicised. Larson and Madura (2003) show that investors only overreact to information when trading based on private information (i.e. uninformed events), consistent with the self-attribution bias outlined by Daniel *et al*. (1998).

[31] The 50 measures are classified under the headings risk, liquidity, price level (relative to accounting numbers), growth potential, and price history.

Larson and Madura (2001) reach the same conclusion when evaluating overreaction in currency markets.

Wongchoti and Pyun (2005) find that the excess contrarian returns to non-S&P 500 NYSE shares are only significant for high-volume stocks. Such returns cannot be explained by time-varying risk and are dominated by winner (glamour) stocks. Such evidence is consistent with the overreaction hypothesis, as stocks whose prices have overreacted to the greatest degree should experience the highest trading volumes. Contrary to the findings of De Bondt and Thaler (1985) and many others, the findings of Wongchoti and Pyun (2005) suggest that investors only overreact to good news.

Dissanaike (1997) concludes that contrarian returns in the UK are consistent with the overreaction hypothesis. Dissanaike (1997) controls for time-varying risk and restricts his sample to large and better-known companies in order to minimise bid-ask bias and the small-firm phenomenon as drivers of reversals. Dissanaike (1999) confirms these findings using a cross-sectional analysis of the UK's Top-500 firms. Similarly, Kang *et al.* (2002) show that short-term contrarian returns in China are predominantly driven by overreaction to firm-specific information.

Ketcher and Jordan (1994) and Liang and Mullineaux (1994) report significant negative abnormal returns following abrupt changes in value/returns, consistent with short-term market overreaction. Fabozzi *et al.* (1995) document significant reversals following large intraday price movements consistent with the preference reversal hypothesis[32]. Reversals are more pronounced following price declines, for small and low volume firms, on Mondays, and in January.

Jegadeesh and Titman (1995) find that short-term contrarian profits are predominantly caused by investors overreacting to firm-specific information. Lai *et al.* (2003) find that contrarian returns on the Kuala Lumpur market are due to overreaction rather than firm size or time-

[32] The preference reversal hypothesis, as postulated by Grether and Plott (1979), constitutes a violation of the axiom of transitivity.

varying risk. Bowman and Iverson (1998) show that contrarian returns in New Zealand are most likely attributable to overreaction as returns are robust to risk, size, seasonals, and bid-ask bounce. Antoniou *et al.* (2006b) reach a similar conclusion when assessing the UK market.

De Bondt and Thaler (1987) argue that overreaction is caused by the market's overreaction to earnings information. Investors exhibit extrapolative expectations by interpreting extreme earnings as being permanent. The prices of firms with extremely good (bad) earnings are pushed too high (low). When earnings mean revert the market recognises its error and prices follow suit. De Bondt and Thaler (1987) show that the earnings and share prices of firms with extreme prior price performance subsequently reverse

Zarowin (1989b, p.1386) criticises the methodology of De Bondt and Thaler (1987), asserting that one can only test overreaction to earnings by examining "share returns *subsequent* to earnings realisations but not *prior* to them". The results of De Bondt and Thaler (1987) are thus "consistent with, but not evidence of, 'earnings myopia'". Zarowin (1989b) shows that a portfolio of shares with the worst earnings history outperforms that of the best performing firms by an average of 16.6% over the subsequent three years. However, the effect is attributable to the size effect. When firms with extremely poor earnings are matched with commensurate high earners evidence of reversals becomes insignificant[33]. The importance of firm size to the winner-loser anomaly is examined in more detail in section 3.7.6.

Empirical evidence consistent with overreaction is not restriced to share price data. Vergin (2001) shows that individuals betting on NFL games overreact significantly to unusually positive past performance. Grant *et al.* (2005), Fung and Lam (2004), Fung *et al.* (2000), and Lin *et al.* (1999) find evidence of contrarian profits in futures market, while Parikakis and Syriopoulos (2008) and Larson and Madura (2001) document reversals in currency markets in both emerging and developed markets.

[33] Furthermore, Zarowin (1989b) shows that among poor performing stocks, smaller winners outperform larger losers.

3.6.2 Noise traders

Chapter two outlined evidence of investors engaging in positive feedback strategies. If such trading drives price beyond their fundamental values, it is natural to expect a subsequent reversal. In essence, the presence of noise traders and the limits to arbitrage can result in an overreaction that is not immediately corrected. After a certain point, sentiment reverses and prices revert towards, and often overshoot, their mean values.

De Long *et al.* (1990) argue that mean reversion is caused by the temporary errors of noise traders. De Long *et al.* (1990) and Chopra *et al.* (1992) argue that the opportunities presented by the winner-loser anomaly may persist because of arbitrageurs' preference for short-term arbitrage opportunities and the fact that contrarian investment strategies require capital commitments over extended periods, usually in smaller firms.

According to Shleifer and Vishny (1990), this preference arises because arbitrageurs are exposed to opportunity costs if there is no certainty that mispricing will be corrected in a timely fashion. Due to the periodic evaluation of money managers by their clients, arbitrageurs flock to short-term arbitrage opportunities. Bloomfield *et al.* (2009) find that in laboratory experiments uninformed traders behave largely as irrational contrarian noise traders, reducing the market's ability to accurately and quickly incorporate new information into prices.

Behavioural biases are not unique to uninformed traders. Covel and Shumway (2005) show that Chicago Board of Trade proprietary traders are prone to loss aversion that results in the assumption of elevated risk levels in the afternoon in an attempt to recoup morning losses. The afternoon prices set by such traders reverse to a much great degree than those of traders with morning gains.

Barros and Haas (2008) postulate that the prevalence of return reversals in place of the momentum returns documented in much of the previous research on emerging markets is driven by the increased amount of information available to investors and the advent of Internet trading. These innovations led to greater information diffusion, overreaction, overconfidence, and a greater influence of small investors, who are more likely to use contrarian strategies[34].

3.6.3 Herding, conservatism bias, and anchoring

Kang *et al.* (2002) show that herding plays an important role in explaining short-term contrarian returns in the Chinese market. The authors state that there is a dominance of individual investors in the relatively young capital market of China. There is a lack of reliable information on firms (particularly small firms) and thus investors tend to rely on technical analysis and rumour. This is accentuated by syndicate speculators who create bullish sentiment on small stocks. These factors combine to create a speculative environment, which leads to herding and causes the prices of small stocks to temporarily overshoot their fundamental values before reverting towards their mean.

Power and Lonie (1993, p.333) argue that stereotyping and inappropriate anchoring prevent investors from fully and impartially recognising changing trends in performance, thereby causing an inertia that prevents prices reaching equilibrium. The bias is gradually eliminated by the accumulation of conflicting evidence and share prices thus reverese. This is analogous to the conservatism bias as postulated by Edwards (1968, cited in Doukas and McKnight, 2005), and discussed in chapter two.

In a laboratory experiment, Cirpirani and Guarino (2005) endow subjects with information on the fundamental value of an asset and the history of past trades. Subjects trade sequentially with a market maker who updates the market price in response to trades received. The study tests for herding behaviour but shows that investors do not tend to mimick the trades of others. Instead, investors often choose to ignore the information that they have been imbued with and either decide not to trade or trade in a contrarian way by trading against the market.

In a similar experimental setting, Drehmann *et al.* (2005) also show that herding is rarely observed when pricing is flexible. There is also ample evidence of contrarian behaviour that

[34] See, for example, Grinblatt and Keloharju (2001a).

prevents prices from converging to their fudamental value. Drehmann *et al.* (2005) rationalise contrarian trading at relatively high or low prices when agents doubt the rationality of other traders.

The disposition effect, as outlined in chapter two, can also explain the phenomenon of return reversal as it describes the tendency for investors to sell winners and hold losers (as purchase price is used as a reference point and investors are reluctant to realise losses). Barber and Odean (1999) assert that the tendency for investors to buy stocks with extreme performance leads to overreaction. Weber and Camerer (1998) present confirmatory evidence of a disposition effect in experimental security trading. Similar evidence is provided by Barber and Odean (1999), Andreassen (1987), and Shefrin and Statman (1985). In the absence of individuals' complete trading records it is difficult to disentangle the disposition effect and negative feedback trading that attempts to exploit mean reversion.

3.7 Rational explanations

This section discusses the explanations that have been postulated to explain 'abnormal' contrarian returns in a manner that is consistent with standard finance theory rather than behavioural biases. The results of De Bondt and Thaler (1985) were controversial and did not go unchallenged. Ardent defenders of market efficiency assert that contrarian returns are more apparent than real, as they result from various model mis-specification and measurement error sources such as inadequate risk measurement, bid-ask spread, illiquidity, transaction costs, survivorship bias, data mining and lead-lag effects. It is also suggested that evidence of return reversals does not constitute a separate anomaly but is merely a manifestation of existing anomalies such as the size effect and the January effect.

Fama (1998) maintains that the approximately equal occurrence of momentum and reversal returns in emprical work is consistent with market efficiency; furthermore, such anomalies are generally not robust to reasonble changes in research methodology. However, if such anomalous returns systematically occur over specific holding periods, i.e. short-term reversals, medium-term continuation, and long-term reversal, then market efficiency is clearly violated. The following sub-sections outline the various rational explanations that have been proposed to explain apparently anomalous returns in a manner that is consistent with market efficiency.

3.7.1 The role of risk

Fama (1998, p.285) asserts that "apparent anomalies are methodological illusions". The main criticism of De Bondt and Thaler's (1985) study is that it assumes that risk levels do not change between the portfolio formation and test periods. Researchers such as Fama and French (1988), Chan (1988), and Ball *et al.* (1995) argue that 'abnormal' returns could be a rational reward for assuming additional risk. In other words, anomalous returns reflect a rejection of asset pricing models such as the CAPM, as opposed to a violation of the EMH. The risk of both losers and winners is not constant and thus the estimation of the return from a contrarian investment strategy is sensitive to the estimation methods employed.

Chan (1988) uses the CAPM and adjusts for changes in risk by calculating a distinct beta for the rank and test periods. Chan (1988) finds that the contrarian strategy earns a very small abnormal return, which is probably economically insignificant and is likely to be a normal compensation for the additional risk involved in such an investment strategy. This is because losers' betas increase between the rank and test period and *vice versa* for winners. It is argued that losers are safer in the beginning but become more risky as their financial leverage becomes larger as stock price falls. Additionally, risk increases because of the loss of economies of scale and increases in operating leverage. These effects reduce the risk of winner stocks as their values increase during the rank period (Chan, 1988).

Fama and French (1992) show that beta alone does not sufficiently explain the cross-sectional variation in stock returns. The inclusion of a firm size and book-to-market (B/M) significantly improve explanatory power. Fama and French (1992) argue that size and B/M are proxies for unobservable common risk factors and conclude that their evidence is consistent with rational assets pricing.

Fama and French (1996) show that contrarian returns are explained by the increased risk of the loser portfolio and can be captured by a multifactor asset pricing model. Galariotis *et al.* (2007) show that contrarian returns in the UK are explained by the Fama–French three factor model. This suggests that reversal returns are driven by size and value rather than behavioural biases and investors are merely rewarded for assuming additional risk.

Clements *et al.* (2009) provide confirmatory evidence of De Bondt and Thaler's (1985) return reversals in out-of-sample testing that augments the seminal study with two decades of return data. Indeed, cumulative excess returns on a risk-unadjusted basis increase to almost 58% for the updated time period, with the loser portfolio contributing all but four percentage points of the returns to the contrarian strategy. The addition of the updated period would increase the overall returns documented by De Bondt and Thaler (1985) by 50%, suggesting that the anomaly is "alive and well" (Clements *et al.* 2009, p.77).

However, Clements *et al.* (2009) show that the above returns disappear when risk is appropraitely accounted for. Consistent with the findings of Chan (1988) for the earlier dataset, Clements *et al.* (2009) show that the beta of losers (winners) increases (decreases) between the portfolio formation and test periods. The three-factor Fama and French model (incorporating the test period betas) shows that size and value drive contrarian returns. Such returns thus appear to be merely a compensation for the additonal portfolio risk that must be assumed by buying losers that tend to be small, distressed stocks.

However, Agarwal and Taffler (2008) find no evidence of a link between financial distress and size and book-to-market factors. Similarly, Richards (1997) finds no evidence that losers are riskier than winners for a contrarian investment strategy on national market indices. Furthermore, reversals are not unique to small markets, although they are generally larger in smaller markets. Similarly, several studies, including Nam *et al.* (2001), Balvers *et al.* (2000), and De Bondt and Thaler (1987) show that risk differentials are incapable of fully accounting for contrarian returns.

Mun *et al.* (2001) argue that a nonparametric approach with time-varying risk in conjunction with a multi-factor CAPM is more appropriate when errors may not be normally distributed. Mun *et al.* (2001) show that contrarian returns are significantly reduced (but remain non-trivial) when such an approach is adopted as parametric tests tend to overstate contrarian returns.

Chopra *et al.* (1992) estimate event-varying betas for the CAPM in computing abnormal returns for winners and losers and show that an adjustment for beta risk explains a large proportion, but not all, of the overreaction effect. Their results are still consistent with a substantial overreaction effect. Using annual (monthly) return intervals, they find that extreme losers outperform extreme winners by 6.5% (9.5%) per annum. They also show that the overreaction effect is distinct from the size effect.

Ball and Kothari (1989) confirm Chan's (1988) assertion that the superior returns to past losers are attributable to elevated risk levels. However, Jones (1993) argues that the beta measuresments of Chan (1998) may be biased as they are only suitable for a one-factor return-generating process. Allen and Prince (1995) find that beta changes between rank and holding periods are trivial in Australia. Similarly, Braun *et al.* (1995) contradict the assertion of Chan (1988) by showing that leverage effects do not lead to a significant change in conditional betas.

Antoniou *et al.* (2006a) use a Kalman filter algorithm (Kalman, 1960) to calculate time-varying systematic risk measures in Greece and find that 'abnormal' returns can be fully explained in the long run by changes in systematic risk. Accordingly, failing to account for the effect of time-varying risk may lead to biased and false evidence against the EMH.

Jordan (2012) considerably extends the dataset employed in previous studies using international indices and shows that the reversal anomaly disappears when a time-varying CAPM and moderate transaction costs are utilised. Jordan (2012) employs conditional alphas in addition to the more commonly utilised time-varying betas. The author finds that time-varying betas alone are incapable of capturing long-tern return reversals; however, the addition of conditional alphas accounts for such reversals even when transaction costs are ignored. Furthermore, even in the absence of risk adjustment, contrarian profits disappear when moderate transaction costs are included. Jordan (2012) concludes that markets appear to be efficient and previously documented long-run return reversals are attributable to transaction costs and time-varying risk.

In contrast, La Porta *et al.* (1997), La Porta (1996) and Lakonishok *et al*. (1994) show that the significantly higher returns to buying value stocks are not merely compensation for bearing additional risk but are due to the unwinding of the naïvely extrapolative expectations or investors.

3.7.2 Measurement errors

There are a number of measurement errors that can result in the discovery of spurious reversals. This sub-section outlines the importance of three such errors, namely; the lead-lag effect, bid-ask bias, and illiquidity. Returns may also be overstated by underestimating transaction costs, as outlined in section 2.4.4.

Lo and MacKinlay (1990a) find that overreaction accounts for less than half of the contrarian profits in the US market. Lo and MacKinlay (1990a) find that part of the excess abnormal returns to the short-term contrarian investment strategy are due to the positive serial correlation in portfolio returns. However, negative serial correlation in individual returns still accounts for a significant portion of the excess abnormal returns. Lo and MacKinlay (1990a) find that the returns of large stocks tend to lead those of smaller stocks but not *vice versa*. This lead-lag effect may be interpreted as evidence of the delayed reaction of smaller firms to news. McQueen *et al.* (1996) show that small stocks display a delayed reaction to common good, but not bad, news, consistent with Keim and Madhavan’s (1995) observation that traders take longer to execute buy orders than equivalent-sized sell orders.

Niederhoffer and Osborne (1966, p.905) argue that short-term reversals may be largely driven by bid-ask spread and limit orders, which “act as a barrier to continued price movement in either direction". When buy and sell orders occur with equal incidence, transaction prices will fluctuate between the bid and offer price until the highest bid and lowest offer are executed. Amihud and Mendelson (1986) show that expected return is an increasing function of bid-ask spread. The bias is particularly pertinent for the small firms that are often central to the generation of contrarian profits and has a greater bearing on short-term reversals.

Chou *et al.* (2007) find that contrarian returns in Japan are due to the lead-lag effect rather than investor overreaction or other behavioural explanations. More specifically, excess abnormal returns are primarily attributable to cross-autocorrelations among firm-specific error components of the Fama-Frech three-factor model. Boudoukh *et al.* (1994) argue that the lead-lag effect may simply be a proxy for the short-term autocorrelation patterns of small stocks. Similarly, Jegadesh and Titman (1993) show that the lead-lag effect is a attributable to investors' delayed reaction to common factors.

Conrad *et al.* (1997) and Boudoukh *et al.* (1994) argue that short-term contrarian profits are due to measurement errors and market microstructure biases such as non-synchronous trading, price discreteness and the bid–ask bounce. Conrad *et al.* (1997) show that when bid prices are used only a small level of profits remain to the strategy and these are subsumed by even trivial levels of transaction costs (generally less than 0.2%). Similarly, Rosenberg and Rudd (1982) show that transaction costs may prevent investors from profiting from negative serial correlation in monthly returns.

Mech (1993) shows that portfolio autocorrelation is due to transaction costs slowing price adjustment. Boudoukh *et al.* (1994) assert that nonsynchronous trading is the main cause of autocorrelation in short-term returns. The authors argue that studies such as Lo and MacKinlay (1990b) understate the effect of nonsynchronous trading as they assume an equal probability of trading in any period and assume that if a stock trades it does so at the closing price. Lo and MacKinlay (1990b) also fail to account for the heterogenity of stocks, i.e. the fact that the probability of non-trading may vary greatly for different stocks. However, McQueen *et al.* (1996) find that nonsynchronous trading accounts for an insignificant portion of autocorrelation in long-run returns.

Cox and Peterson (1994) find evidence of significant short-run reversals in the US. However, they show that such reversals are primarily driven by bid-ask bounce, firm size, and market liquidity rather than overreaction. Stocks with large one-day price declines continue to perform poorly over an extended period. Similarly, Park (1995) shows that short-term price reversals disappear when the average of bid-ask prices is employed and transaction costs are accounted for.

Bremer and Sweeney (1991) speculate that the reversals of low-priced stocks can be caused by the oscillation between bid and ask prices. Kaul and Nimalendran (1990) show that there is a negative relationship between stock price and bid-ask spread and find that short-run reversals in the US are attributable to bid-ask bias and a lead-lag effect. Kaul and Nimalendran (1990) show that evidence of market overreaction disappears when bid-to-bid prices are used to calculate weekly returns.

Bid-ask bounce is a related but separate phenomenon to bid-ask spread. It refers to the situtation where successive prices bounce between bid and ask (or *vice versa*) giving the illusion of a price change (or exaggerating actual price changes). It is particualry relevant for small, illiquid stocks. If a stock price remains unchanged over a specified period after light trading, there is a 50% chance of returns appearing to be negatively autocorrelated as returns are measured using closing prices.

Conrad and Kaul (1993) also assert that contrarian profits may be overstated because of bid-ask errors, nonsynchronous trading and price discreteness[35]. The authors argue that the method of cumulating single-period returns over long intervals upwardly biases the results of long-term overreaction studies as it involves cumulating measurement errors. Using almost identical data to De Bondt and Thaler (1985), Conrad and Kaul (1993) show that contrarian returns disappear for all months except January when average cumulated abnormal returns are replaced with the average holding period abnormal returns.

[35] Conrad and Kaul (1993) show that measurement biases are more pronounced if, as is primarily the case, losers are small stocks and winners are large stocks as there is a nonlinearity in the relation between bias and price.

Conrad and Kaul (1993) conclude that evidence of overreaction is thus driven by measurement errors and the January effect. The main source of the measurement error is an upward bias in the return of past losers. Furthermore, this bias is correlated to price as opposed to firm size. Conrad and Kaul (1993) show that loser stocks have an average (minimum) price of $11.48 ($1.62), while winners register equivalents of $38.58 and $9.32, respectively. Furthermore, over 10% of loser firms had average prices less than $1[36].

Conrad and Kaul (1993) find that the returns to a strategy based on price (buying low-priced stocks and short-selling high priced stocks) are two to four times larger than those to a contrarian strategy based on prior returns. However, such returns are limited to January, suggesting that the January effect is a low-price phenomenon (perhaps due to tax-loss selling). Galariotis *et al.* (2007) show that failing to account for non-synchronous trading and the bid-ask spread leads to the number of profitable contrarian strategies increasing by more than 100%.

However, Loughran and Ritter (1996) suggest that the concerns of Conrad and Kaul (1993) may have been overstated due to survivorship bias and long-term mean reversion. The authors find that the difference between cumulative abnormal returns and buy-and-hold returns and the influence of low-priced stock are both limited. Loughran and Ritter (1996) assert that bid-ask spread biases are not compounded over time and argue that price proxies for prior returns (and possibly risk) as well as bid-ask spread percentages. Furthermore, Mazouz and Li (2007) document substantial reversal returns in the UK using both buy-and-hold returns (BHAR) and cumulative abnormal returns (CAR).

Similarly, Power and Lonie (1993) argue that recording errors in bid and ask prices are more pronounced for high-frequency data than for the monthly data typically employed in long-term overreaction studies. Furthermore, the biases outlined by Conrad and Kaul (1993) "may offset rather than reinforce each other" (Power and Lonie, 1993, p.334). Power and Lonie (1993) also point out that it is the exclusion of January, as opposed to the attempted

[36] Conrad and Kaul (1993) show that a $1 stock has a measurement bias of 56.25%. The equivalent for a $3 stock is only 6.25%.

correction for bid-ask bias, that materially alters the returns to the contrarian strategy[37]. Boynton and Oppenheimer (2006) find that controlling for survivorship bias and bid-ask spreads results in substantial reductions in contrarian returns. However, such returns remain economically significant.

Additionally, Power and Lonie (1993) assert that bid-ask bias may be specific to US studies that utilise the CRSP database. The Datastream resource used in other studies (such as Power *et al.*, 1993) uses mid-market share prices, thereby reducing the spread bias. In fact, Power *et al.* (1991) show that contrarian returns in the UK are more impressive when the alternative cumulating procedure of Conrad and Kaul is used than the equivalent returns generated using De Bondt and Thaler's (1985) methodology. Similarly, Schiereck *et al.* (1999) present evidence of economically and statistically significant contrarian returns in Germany, a market which they claim has no explicit bid-ask spreads.

Fama (1998) states that bad-model problems are more pronounced in tests of long-term returns as expected returns are an increasing function of time. In contrast to Conrad and Kaul (1993), Fama (1998) argues that such returns should be calculated using sums or averages of short-term abnormal returns rather than buy-and-hold abnormal returns, as compounding returns to obtain the latter can result in exaggerated returns and cause statistical problems such as extreme skewness[38]. Fama (1998) further advocates the use of value-weight returns, as equally-weighted returns give relatively more weight to small stocks, which poses more significant problems to asset-pricing models. Furthermore, value-weighted returns more accurately reflect the total wealth effects of investors.

Fluck *et al.* (1997) focus on large companies in order make transaction cost estimates more reliable and to minimise the problem of survivorship bias. Fluck *et al.* (1997) show that a low P/E contrarian strategy yields sizeable risk-adjusted excess returns after accounting for

[37] The alternative cumulating procedure results in a decrease in returns from 37.5% to 27.1%. On the other hand, returns for non-January months fall from 12.2% to -1.7% when Conrad and Kaul's cumulating procedure is employed.

[38] Fama (1998) points out that many asset pricing models assume normally distributed returns. Short-term returns are more likely to exhibit normality as skewness is more pervasive in longer-term returns.

transaction costs and bid-ask spreads. The results are robust to out-of-sample testing and are not driven by investors overestimating the future earnings of glamour stocks, as suggested by Lakonishok *et al.* (1994).

Ball *et al.* (1995) show that contrarian strategies rely heavily on past losers that are generally low-priced small firms. The returns of such firms are skewed and the success of the strategy is sensitive to the effects of microstructure effects such as bid-ask spreads, liquidity, and brokerage fees. Furthermore, abnormal returns may be due to model mis-specification as low-priced losers are generally purchased after bear markets and are thus subject to expected-return effects as highlighted by Jones (1993). Ball *et al.* (1995, p. 55) report that "... bid–ask bias explains approximately two-thirds of the following-week profits from a contrarian strategy."

Several studies show that such microstructure biases are most severe at the turn of the year, which is the time of portfolio formation for the majoirty of contrarain studies[39]. In light of this, Ball *et al.* (1995) use June-end investment periods and report that contrarian returns are 31% lower that those for their December-end equivalents. These findings call into question the robusteness of the contrarian returns documented by, *inter alios,* De Bondt and Thaler (1985).

Akhigbe *et al.* (1998) find no significant profits from a short-term contrarian strategy on the NYSE. The authors analyse the returns to shares in the five days following their appearance in the *Wall Street Journal* gainers and losers list. The authors use bid-ask spread to control for transaction costs and find significant reversals during the post-announcement period. However, any profits from exploiting this reversal are eroded by transaction costs, thereby supporting the weak-form efficiency of the NYSE.

Atkins and Dyl (1990) find that the average bid-ask spreads are larger than reversals and thus the market is efficient. They use the average of the May and December bid-ask spreads surrounding the date the stock experienced the large price change. Akhigbe *et al.* (1998)

[39] See, for example, Roll (1983); Lakonishok and Smidt (1984); and Keim (1989).

improve on this methodology by using contemporaneous trade and quote date (i.e. bid-ask spreads from the days immediately following the announcements). Akhigbe *et al.* (1998) find that losers make positive abnormal returns on each of the two days immediately following the event. Winners increase in value on the first day after the announcement but experience a reversal on days two through four. This is similar to the pattern of continuation followed by reversal found in studies of a longer-term contrarian investment strategy (De Bondt and Thaler, 1985), or in Poterba and Summers' (1988) study of mean reversion, albeit over a short-term horizon.

Lee *et al.* (2003) unearth similar results to Akhigbe *et al.* (1998) for the Australian market. The authors examine weekly share prices and find structure in returns; however transaction costs eliminate any potential profits. However, the authors argue that the strategy may still be of use to fund managers as an overlay on their existing portfolio strategy as they effectively face a zero incremental transaction cost. The predictability in stock prices is primarily caused by an overreaction to firm-specific information. Furthermore, the size of any contrarian profit is negatively related to company size, highlighted by the fact that contrarian profits are lower when the value-weighted portfolio methodology was used. The authors argue that their results are not explained by time-varying risk, seasonality factors, or trading volume.

Returns reversals may also persist due a lack of liquidity, particularly in loser stocks, which tend to be small stocks on average. Chordia *et al*. (2002) report a strong positive relationship between order imbalances (buy orders less sell orders) and market declines, which suggests that investors are contrarians on aggregate. Order imbalances reduce liquidity and have a significant impact on market-wide returns. The authors also present evidence of reversals following large market declines and continuation following postive returns.

Lo and Coggins (2006) test this hypothesis by examining whether order imbalances following large price changes are the cause of short-term return reversals and find that return reversals are positively related to the level of order imbalance. Gaunt (2000) finds that modest contrarian returns in Australia are dominated by the a loser portfolio that mainly contains small stocks and that such returns cannot be exploited due to a lack of liquidity.

Surprisingly, Hameed and Ting (2000) show that the profits to a short-term contrarian strategy in Malaysia are greater for stocks that are more actively and frequently traded[40]. Bailey and Gilbert (2007) show that a value strategy, as presented by Cubbin *et al.* (2006), remains profitable in South Africa after accounting for liquidity concerns by showing that the value strategy produced lower, yet still economically significant, returns when applied to more liquid shares alone.

Conrad *et al.* (1994) examine the link between lagged trading volume and short-term autocovariance in returns and show that high-volume (low-volume) stocks experience price reversals (continuations). The effects are shown to be more pronounced for small stocks. Bremer and Hiraki (1999) present assenting evidence for Japanese stocks.

3.7.3 Survivorship and selection bias

The problem of survivorship bias is acute in any study of return reversals as past losers, in particular small firms, are more likely to disappear from the sample. The missing test-period returns of firms that delist due to bankruptcy are thus likely to upwardly bias the returns to a contrarian strategy. Of course, the opposite may be the case for firms that disappear due to merger or acquisition activity. Indeed, Galariotis *et al.* (2007) shows that survivorship bias reduces the number of profitable contrarian strategies in the UK.

The sample of firms that are available in the databases used in many studies can introduce considerable bias, especially when the characteristics of delisted firms differ systematically from those that survive. This bias is of particular relevance for studies of long-term market behaviour. Brown *et al.* (1995) show that tests of serial autocorrelation in returns are biased towards the rejection of a random walk due to survivorship bias. Banz and Breen (1986) and Kothari *et al.* (1995) claim that the value returns documented in many studies may be

[40] However, the authors note that even modest transaction costs would erode the profits to the strategy.

attributable to survivorship and look-ahead bias associated with the COMPUSTAT database[41].

If the majority of firms delist because of financial distress, it follows that returns will be biased upwards. Firms in financial distress are likely to be small, risky firms that have relatively poor recent returns. By excluding such firms from a sample the average returns (risk) of the remaining risky firms will be overstated (understated). As Bain (1972, p.104) asserts: "the use of *ex-post* sampling will invariably produce an upward bias in the measurement of returns on risky securities". Since the delisted firms are more likely to be classified as past losers, the returns to the contrarian strategy are likely to be overstated due to this survivorship bias.

Davis (1996), Kothari *et al.* (1995), and Banz and Breen (1986) confirm that the returns on shares excluded from the COMPUSTAT database are lower that those of survivors. Davis (1996) further shows that delisted firms tend to be smaller than those that remain in the database. However, it is noteworthy that McElreath and Wiggins (1984) find that 55% of the delistings from the New York Stock Exchange (NYSE) between 1970 and 1979 were due to mergers, with a mere 6% being attributable to bankruptcy and liquidations. Accordingly, the authors conclude that the importance of survivorship bias may be overstated. Similarly, Ball and Watts (1979) show that survival bias had little effect on EPS data as there is no significant difference between the EPS of surviving and delisted firms.

Selection and survivor bias is more relevant for contrarian strategies based on accounting measures than those based on past price performance as the COMPUSTAT database, which is primarily used to collect accounting information, is prone to greater biases than the CRSP database that is used to collect prices[42].

[41] However, significant returns to value strategies have been documented by studies that use databases that are not subject to the same biases (for example La Porta, 1996) and those that carefully minimise such biases (for example La Porta *et al.,* 1997).
[42] For a discussion of the biases associated with the COMPUSTAT database, see Gilbert and Strugnell (2010); McElreath and Wiggins (1984); and Ball and Watts (1979).

The profitability of the the value strategy in South Africa, as presented by Bailey and Gilbert (2007) and Cubbin *et al.* (2006), cannot be attributed to survivorship bias as both studies include delisted shares. Gilbert and Strugnell (2010) extend the time period used by those studies and test whether the expensive and time-consuming efforts of those two South African studies in collecting data on delisted shares was justified. Gilbert and Strugnell (2010) show that survivorship bias has a material impact on the returns to value strategies. Although mean reversion remains present, it is more significant for a sample of currently listed shares than a portfolio of all shares. It thus seems crucial that every effort is made to minimise survivorship bias and this study aims to do so by including delisted firms.

3.7.4 Mean reversion and the business cycle

There is a considerable body of evidence suggesting that share prices revert towards a mean value over the medium term. It is thus plausible that contrarian returns are not driven by overreaction but are attributable to returns synchronsing with this pattern and portfolios being formed near or at the turning points in returns. Forbes (1996) strongly advocates a synthesis of the literatures relating to mean reversion and return reversal given the interrelated nature of the two phenomena. If returns follow a mean-reverting trend it is evident that the chance of not finding return reversals is minimal as it would require commencing the test at approximate mid-point of an up or down state (so that the holding and test period returns are insignificant as the returns within each period largely cancel each other out).

Poterba and Summers (1988) examine share prices in 18 countries and find that in most countries, share prices are mean reverting with significant negative serial correlation of returns in the long run, i.e, poor performance over a specific period is generally followed by good performance and *vice versa*. The authors find that in the short-term, i.e., less than one year, there is positive serial correlation of returns. Poterba and Summers (1988) find a large transitory component in stock prices, most likely caused by noise traders. Fama and French (1988) document similar evidence of the long-term mean-reverting nature of returns but argue that mean reversion is due to time-varying expected returns, consistent with EMH. In terms of a contrarian investment strategy, the key for an investor is to know the optimal length of formation and holding period so that losers are purchased as their prices reach a trough and sold when their share price has peaked.

Gallagher and Taylor (2000) provide further robust evidence of mean reversion in US stock prices. Renshaw (1984) shows that companies that suffer large back-to-back declines tend to subsequently outperform the market, consistent with mean reversion. Hirschey (2003) presents further evidence of mean reversion in the S&P 500 and NASDAQ indices. Reversals are considerably more pronounced following bear markets. Similarly, Ismail (2012) and Chen *et al.* (2012) find that contrarian returns are larger following down markets in Egypt and China respectively.

Gallagher *et al.* (1997) and Gallagher (1999) provide further evidence of mean reversion, in the form of a transitory component in stock price, in sixteen markets. Kim *et al.* (1991) show that mean reversion is mainly a pre-war phenomenon and may be due to the assumption of normally distributed returns. However, McQueen and Thorley (1991) use Markov chains to show that low (high) returns tend to follow sequences of high (low) returns in post-war years. Balvers *et al.* (2000) find similar results when examining mean reversion in 18 countries for the period 1969-1996; mean reversion having a half-life of three to three-and-a-half years. The authors conclude that contrarian investment strategies that fully exploit such mean reversion across national indices outperform buy-and-hold strategies. Gropp (2004) reaches the same conclusion using the 1926-1998 time period.

It is thus often argued that return reversals are merely a manifestation of the mean-reverting nature of stock returns. If returns are normally distributed, then one would expect that a sample of extreme performing stocks (an asymmetric sample) is more likely to be followed by sample of stocks with returns closer to the population mean. Such a reversion towards the mean may be misinterpreted as evidence of overreaction to news. However, although the terms ‘mean reversion’ and ‘return reversals’ are often used interchangably, the terms are not necessarily synonymous. The empirical evidence shows that returns are manifestly above the population mean in the portfolio holding period. In other words, returns tend to systematically overshoot the population mean, switching from the extreme losers to winner group, rather than merely falling back in line with the average return.

Afterall, if returns merely reverted closer to the population mean, a contrarian investment strategy would not generate abnormal returns, regardless of the magnitude of the reversal. The absence of an observed mean reversion, *ex post*, would naturally require an improbable level of continuation. If one observes the worst performing stock over a specific period, it is highly unlikely that the same stock will maintain such a poor performance. A reversal towards the mean is thus almost inevitable. However, the stylised finding that returns overshoot the mean is suggestive of overreaction rather than mean reverison.

To conclude, mean reversion and return reversals are inextricably linked. Mean reversion tends to define aggregate market trends, while contrarian strategies succesfully sort stocks on an individual basis and often over a shorter time period. Noise traders often prevent the timely reversion to mean values, thereby presenting contrarian profit opportunities. Evidence of short-term contrarian returns are unlikely to be explained by mean reversion as the probability that such short-term strategies are executed at the turning point of a long-term mean reverting cycle is minimal.

3.7.5 Seasonality and data mining

This section outlines the importance of seasonality in explaining contrarian returns and also examines the consistency of return reversals over time in light of data-mining issues. It is axiomatic that January returns contribute disproportionally to the overall profits of long-term contrarian strategies. It is therefore a matter of interest to examine whether the winner-loser anomaly merely constitutes a repackaging of the January effect.

Several studies, such as Bildik and Gulay (2007), Conrad and Kaul (1993), and Zarowin (1990), show that contrarian returns are largely confined to January. Jegadeesh (1991) shows that the mean reversion phenomenon is entirely unique to January. The majority of the contrarian returns unearthed by De Bondt and Thaler (1985) are confined to January (especially for loser stocks); however, overreaction is also prevalent in non-January months. De Bondt and Thaler (1985) suggest that tax-loss selling is the most plausible explanation for their sizeable January returns as the relative returns to the loser portfolio decline between October and December. However, the price rebound in January is more pronounced than the preceding declines and elevated January returns persist for five years.

Johnston and Cox (1996) argue that tax status may be more pertinent than behavioural bias in structure of ownership, as argued by Chopra *et al.* (1992). Tax-loss selling can be of significant use to individual investors but is not relevant to institutional investors. Consequently, if small firms have a greater proportion of individual investors it follows that small firms are more likely to earn elevated January returns.

Zarowin (1990) shows that contrarian returns disappear for all months except January for size-matched portfolios. Zarowin (1990) argues that the tax-loss selling hypothesis may explain the uniqueness of the January returns. Johnston and Cox (1996) empirically confirm that tax-loss selling in January is a key contributor to long-term price reversals. In contrast, Bremer and Sweeney (1991), De Bondt and Thaler (1985, 1987) and others show that the overreaction effect is a separate phenomenon by documenting significant non-January returns.

Jegadeesh (1991) concludes that tax-loss selling cannot fully explain elevated January returns as mean reversion is only observed in January in the UK, where the tax year ends at the beginning of April. However, contradictory evidence is provided by Campbell and Limmack (1997), who show that return reversals are dominated by the January and April returns of small loser stocks, consistent with the tax-loss selling hypothesis. Ahmad and Hussain (2001) find that February plays a key role in contributing to long-run reversals in Malaysia[43]. Since the tax year does not end in February the authors postulate that the effect may be caused by window dressing, menal accounting, or the spending of *Ang Pows* (cash gifts

[43] Ho (1990) and Wong *et al*. (1990) provide evidence of a February (Chinese New Year) effect for Asian markets.

tradionally exchanged at the turn of the Chinese new year), as Chinese investors are the dominant investors in the Malaysian market.

The accusation of data mining is often the first port of call for propoents of the EMH when attempting to explain away apparently anomalous returns[44]. Black (1993, p.37) outlines the perils of data mining and states that anomalies may be "nuggets from a gold mine, found by one of the thousands of miners all over the world". Fama (1998, p.287) claims that "chance generates apparent anomalies that split randomly between overreaction and underreaction". The majority of studies report average contrarian returns over extended periods of time, commonly in excess of 50 years. It is possible that these averages are driven by a small number of sub periods.

Chen and Sauer (1997) examine the stability and persistence of the overreaction anomaly and find that past losers outperform past winners by approximately 11% annually over a 66-year period. Abnormal returns decline as one moves from the extreme loser portfolio to the extreme winner portfolio. When the returns are broken into sub-periods, the authors find positive profits in the pre-war period, negative profits in the Great Depression era, and no abnormal profits from 1940s to mid-1950s. Negative abnormal returns are also documented after the mid-1980s and overall the lack of consistency in contrarian returns calls into question the robustness of reversals returns. Furthermore, the majoirty of the returns disappear after risk is taken into account.

Bird and Whitaker (2003) show that contrarian returns are only present in major European markets during the market correction at the turn of the 21st century, with momentum profits dominating in the preceeding rising market conditions. In contrast, Paškevičius and Mickevičiūtė (2011) show that a contrarian strategy executed on Lithuanian stocks are only viable in pre-financial crisis periods of rapid economic expansion. Contrarian returns are non-existent in the wake of the financial crisis.

[44] For discussions on the importance of data mining see, for example, Lovell (1983) and Lo and MacKinlay (1990).

3.7.6 Size effect and firm-specific attributes

As outlined in section 3.7.1, Fama and French (1992) show that size plays an important role in explaining cross-sectional differences in expected returns. Accordingly, any return reversals documented in studies that fail to adjust for size may merely represent a manifestation of the size effect.

Archival evidence strongly suggests that the overreaction effect is not homogeneous across size groups. Zarowin (1990) argues that losers outperform winners because they tend to be smaller sized firms than winners at the end of the rank period. Zarowin (1990) shows that losers only consistently outperform winners when they are smaller and the opposite is the case when past winners are smaller. Return differentials between winners and losers disappear for all non-January months when portfolios are matched on size. Hence, evidence of long-run overreaction may be merely a manifestation of the size effect as documented by Banz (1981). However, Zarowin (1989a and 1990) shows that risk-adjusted short-run return reversals are not subsumed by the January or size effect and concludes that the anomaly appears to be genuine and unique[45].

For proponents of the EMH, declaring that an anomaly is attributable to the size effect as opposed to overreaction, underreaction, or any other behavioural bias may appear analogous to rearranging the deckchairs on the Titanic. From the point of view of those who are opposed the idea of efficient markets, an anomaly by any other name would smell as sweet. However, the size effect can be neatly accounted for with reference to risk, bid-ask spread, illiquidity, etc. Accordingly, removing an anomaly from a behavioural dossier to one based on size aligns it more closely to rational explanations consistent with standard finance theory. As Zarowin (1989b, p.1386) argues, "… stock market overreaction is an efficient markets anomaly, the size phenomenon is more likely a CAPM anomaly."

Locke and Gupta (2009) find that firm size plays a crucial role in explaining the substantial abnormal returns to the contrarian strategy in India. Clare and Thomas (1995) also find that the overreaction effect in the UK is subsumed by the size effect; while Wang and Xie (2010)

[45] However, Zarowin (1989a) does caution that the results may be driven by bid-ask bounce.

show that contrarian returns on the Chinese equity market are a decreasing function of firm size. Jegadeesh and Titman (2001) also report significant reversals for small firms only in the US.

Albert and Henderson (1995) argue that there is a bias in the ranking technique used by Zarowin (1990). After correcting for this bias, Albert and Henderson (1995) find that the overreaction effect is distinct from the size effect. Similarly, Dissanaike (1997, 1999, 2002) finds that the winner-loser anomaly could not be explained by the size effect in the UK. Many studies now attempt to control for the size effect by using the Fama-French three-factor model.

Assoe and Sy (2003) show that short-term contrarian returns in Canada are primarily driven by small firms' January returns and do not remain economically profitable after accounting for transaction costs. Bildik and Gulay (2007) find significant contrarian returns in Turkey but conclude that such returns are due to the January effect and the additional risk associated with buying small loser stocks Baytas and Caciki (1999) show that portfolios constructed on the basis of average price significantly outperform those based on size and the traditional contrarian strategy. This may be a manifestation of the size effect as price can be viewed as a proxy for size. Indeed, Kaul and Nimalendran (1990) document a strong positive correlation between market value (size), share price and volume. Chopra *et al.* (1992) find that contrarian returns are much more pronounced for small firms. They posit that small firms are mainly held by individuals while large firms are predominantly held by institutional investors and that the former are more prone to overreaction than the latter. In contrast, Pettengill and Jordan (1990) show that reversals are most pronounced in large firms and are largely confined to January.

De Bondt and Thaler (1987, p.579) show that, although loser firms tend to be smaller than winners, they are nonetheless medium- to large-size firms on average and "the winner-loser effect is not primarily a size effect". Fama and French (1988) corroborate these findings, suggesting that return reversal is not purely a small-firm phenomenon. Ahmad and Hussain (2001) show that the contrarian returns on the Malaysian stock market are not merely a manifestation of the size effect. Campbell and Limmack (1997) provide supportive evidence for the UK market and Chang *et al.* (1995) show that short-term reversals in Japan are not explained by firm size or seasonality.

Peterson (1995) shows that reversals in the three days subsequent to a large one-day stock price decline are significantly lower for firms with exchange-traded options. Such options appear to speed up the price-adjustment process and dampen overreaction, thereby enhancing market efficiency and/or liquidity. Firm size may be viewed as a proxy for option listing as larger firms are more likely to have listed options.

Ibbotson *et al.* (1997) argue that the betas of small firms are underestimated by the standard estimation procedure. The authors posit that it takes longer for market-wide information to be incorporated in their stock prices. It is thus more apposite to estimate beta using the sum of the regression coefficients of the stock's return regressed on the current and one-period lagged market return. Ibbotson *et al.* (1997) present empirical evidence of a negative correlation between this measure of beta ('sum beta') and firm size and conclude that traditional beta measurements fail to capture size risk, thereby partially explaining the small firm effect.

Documented long-term return reversals tend to be primarily driven by the positive returns to past losers. For example, De Bondt and Thaler (1985) show that the returns to losers are three times larger than the winners' equivalent. Similar results are reported by, *inter alios,* Campbell and Limmack (1997), Pettengill and Jordan (1990), Clements *et al.* (2009), and Chopra *et al.* (1992). Indeed, Brailsford (1992) is the only notable study that reports reversals for past winners only. However, short-term reversals are most often observed for both winners and losers (see, for example, Zarowin 1989a).

The stylised dominance of the loser portfolio is consistent with many of the explanations postulated in this chapter. For example, the overreaction literature suggests that agents overreact more to bad news. Additonaly, the size effect, illiquidity, lead-lag effect and bid-ask bias are more pertinent as, *ceteris paribus,* past losers are more likely to be small firms at the end of the rank period. Furthermore, seasonailties such as the January effect tend to be more pronounced for small stocks and survivorship bias is also more pertinent to past losers. Finally, model mis-specification whereby risk is underestimated (or is assumed to be stationary) is more relevant to past losers.

The dominant role that past losers play in driving contrarian returns renders short-selling constraints virtually irrelevant as the strategy involves buying such poor performing stocks and the inability to short sell past winners will often have a neglible (and even positive) influence on trading returns.

3.8 The role of analysts

Contrarian returns can be explained by financial professionals' tendancy to overreact (De Bondt and Thaler, 1990), as outlined in section 3.3. Furthermore, Bauman and Dowen (1988) show that contrarian returns result from prices reflecting analysts' biased long-term earnings growth forecasts. Similarly, Dechow and Sloan (1997) show that over half of contrarian returns are attributable to investors' naïve reliance on analysts' biased forecasts of earnings growth. In light of the fundamental role that analysts play in forming expectations and influencing trading behaviour, chapter four is devoted to examining the link between the behaviour of analysts and the two anomalies under review in this thesis.

3.9 Summary and conclusions

This chapter outlined the evidence relating to the pervasive winner-loser anomaly. The crucial distinction between short- and long-term overreaction was highlighted and rational and behavioural explanations for the apparantly anomalous returns to contrarian stretegies were outlined. The evidence in favour of the anomaly is consistent across geographical, temporal, and methodoglical partitions. Rational explanations are incapable of sufficiently and consistently accounting for the burgeoning body of evidence documenting return reversals.

This chapter has shown how the behavioural biases documented in the psychological literature manifest themselves in the behaviour of investors and analysts, aggregate to the market level and survive due to limits to arbitrage. Stock market participants are particularly prone to the phenomenon of overreaction that is also witnessed in experimental psychology and betting, futures, and currency markets. Overreaction is more prevalent and pronounced in response to bad news and is the most plausible single explanation of long-run reversals, whereas short-run reversals are more attributable to by microstructure biases.

As with momentum returns, there is no single cause that consistently accounts for return reversals and many of the causes are inextricably intertwined. In the same manner that Fama (1998) argues that an approximately equal occurrence of evidence in favour of momentum and reversal is consistent with market efficiency, the inability of any one theory to consistently account for contrarian returns may suggest the that opposite is true. The analysis of contrarian returns for the four markets under review in this study will aim to incorporate as many of the postulated casues as is practical.

Chapter Four

The Role of Security Analysts

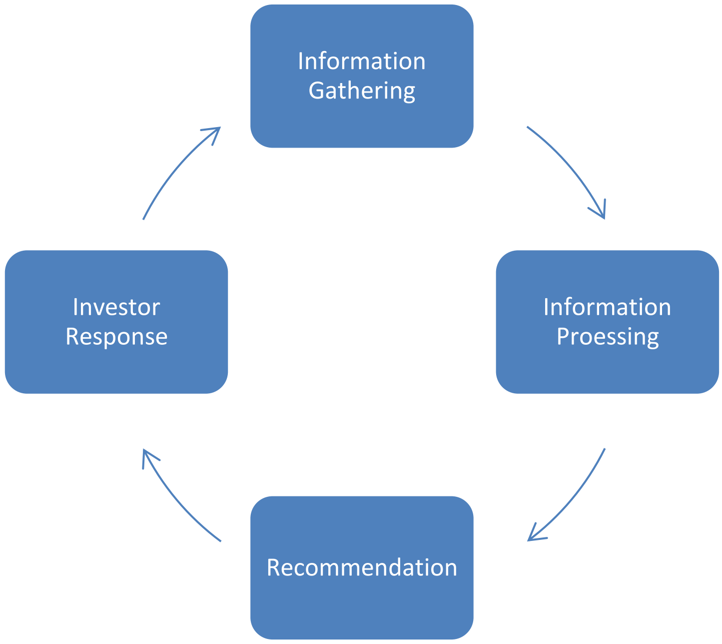
4.1 Introduction

Brokers and analysts play an important intermediary role in financial markets; facilitating trade and providing investment advice. The earnings forecasts of analysts are a key input into equity valuation models and their behaviour can have a significant impact on the allocation of scarce financial resources. There are four main steps in the dissemination of information from companies to shareholders and consequently to share prices, as shown in figure 4.1. First, analysts must garner information from firms; second, they must analyse this information and quantify its impact on earnings and share prices; third, they must communicate this to their clients; and finally these investors must process the information and decide on an appropriate trading response.

Figure 4.1

Anatomy of the information dissemination process

The diagram presents the circular information dissemination process from brokers to investors.



The process is cyclical in nature, as the actions of investors influence the companies followed and the recommendations made by analysts, due to analysts' tendency to follow firms with existing momentum (see section 4.7). During each of these steps different characteristics, behaviours and biases of market participants have a significant impact on the dissemination process and the dynamics of any stock price reaction.

The transfer of information from firm to analyst is affected by the proximity of the analyst to the covered company and any underwriting relationship that may exist between the company and the brokerage house in question. There is also great scope for variation in how the analyst processes the information that is garnered from the covered firm, as analysts are subject to numerous cognitive biases such as overconfidence; overreaction; herding; biased self-attribution; and framing[46]. At the third stage conflicts of interest may result in analysts releasing overoptimistic forecasts and recommendations in order to curry favour with the companies that they cover. Furthermore, the timing of the release of information has important implications for the dynamics of investors' trading responses. Finally, investors respond to the output of analysts in various ways, resulting in an inconsistent impact on share prices. Investors may not be aware of analysts' conflicts of interest, may react in a delayed fashion, and are subject to the same range of cognitive biases that alter the behaviour of analysts.

While there is mixed evidence on the accuracy of the output of brokers, there is consensus that their actions have a significant effect on share prices. The evidence shows that brokers' recommendations induce trading and that their earnings forecasts not only affect share prices as earnings are announced, but also affect the behaviour of covered companies. Thus, brokers have an important role in explaining any stock market anomaly, in particular the momentum anomaly, as there is abundant evidence that brokers follow momentum strategies. If investors follow brokers' recommendations that are based purely on momentum then it is reasonable to expect that share prices may be pushed beyond their fundamental values, thereby leading to reversal in the longer term. This chapter primarily outlines the role of brokers in contributing towards the momentum anomaly. In most cases, the argument can be

[46] See, for example, Welch (2000); Stotz and von Nitzsch (2005); and De Bondt and Forbes (1999).

extrapolated to explain contrarian returns that result from the unwinding of momentum returns that overshoot fundamental values.

The behaviour of sell-side analysts/brokers can 'explain' the momentum anomaly in three ways. First, brokers have conflicts of interest and are more likely to issue buy recommendations (Michaely and Womack, 2004) and are slow to revise their earnings forecasts downwards (Erturk, 2006). Second, herding behaviour can cause stocks to deviate from their fundamental value (Caparrelli *et al*., 2004). Finally, like all investors, brokers' behaviour can be subject to cognitive biases that contribute to momentum returns such as overconfidence, biased self-attribution, and underreaction (see, for example, Stotz and von Nitzsch, 2005). In order for these behaviours to impact share prices and potentially cause momentum investors must take the output of brokers at face value and trade in such a manner that causes the continuation of past performance. This chapter provides an extensive body of evidence consistent with such behaviour by brokers and the requisite response from investors.

The remainder of this chapter is organised as follows. Section 4.2 examines the role of security analysts; section 4.3 examines the accuracy of their forecasts; and section 4.4 outlines the volume and share price implications of the output of brokers. Section 4.5 details the conflicts of interest that analysts and firms face and the regulatory efforts intended to mitigate such conflicts. The propensity of brokers to engage in herding and momentum trading are examined in sections 4.6 and 4.7 respectively, while section 4.8 examines the role of cognitive biases in explaining analysts' behaviour. Section 4.9 discusses the importance of geographical considerations and section 4.10 draws some conclusions.

4.2 The role of security analysts

Security analysts and brokers[47] provide valuable intermediary services such as trade facilitation, information gathering, and investment advice at cost savings to individual investors due to economies of scale and privileged access to pertinent information. Schutte

[47] The terms 'analyst' and 'broker' are generally used interchangeably in this chapter. However, in sections where underwriting fee incentives are pertinent, a distinction is made between buy- and sell-side analysts.

and Unlu (2009) find that greater analyst coverage results in less noise in stock prices, thereby increasing market efficiency and creating a more certain environment for firms to make decisions relating to dividends, investment, capital structure, and corporate acquisitions. Brennan and Subrahmanyam (1995) show that increased analyst coverage improves market depth, consequentially reducing the adverse selection costs of trading, while Brennan *et al.* (1993) show that stocks with greater analyst coverage react more rapidly to common information, thereby enhancing the informational efficiency of the market. Alford and Berger (1999) also show that greater analyst coverage is associated with higher forecast accuracy; while Anand *et al.* (2006) and Irvine (2003) show that recommendation changes and initiations enhance liquidity.

Jensen and Meckling (1976) argue that security analysts have a role in mitigating the agency problem that stems from a separation of ownership and control by reducing informational asymmetries between managers and outside investors. Chung and Jo (1996) posit that analyst coverage reduces agency costs as the public nature of analysts' output motivates and disciplines corporate managers. Thus, increased analyst coverage should result in prices trading close to their fundamental values. Moyer *et al.* (1989) empirically confirm that analysts' monitoring role reduces agency costs; while Merton (1987) shows that a firm's market value is an increasing function of investor cognisance, i.e. the number of investors who are aware of the firm.

However, these findings may be the result of spurious correlation or reverse causation. In light of brokerage pressures, analysts have incentives to follow high quality companies as the stock of such firms is more marketable. Furthermore, Lang and Lundholm (1996) show that analysts tend to follow firms with informative disclosure policies. Thus, the observed reduction in the noise component of covered firms may be attributable to a selection bias rather than analysts playing a pivotal role in disentangling complex financial data.

Naturally, analysts are not rewarded for reducing agency and transaction costs but are compensated for generating underwriting fees. However, increased market efficiency and reduced agency costs may be a by-product of the information that analysts gather and disseminate. Hong *et al*. (2000) confirm this to a certain degree by showing that momentum returns are greater for firms with low analyst coverage, confirming the gradual information-diffusion model of Hong and Stein (1999). Moreover, Wang and Xie (2010) show that contrarian returns in China are only significant for firms with low analyst coverage (a proxy for the speed of information diffusion).

However, there is an extensive body of literature that suggests that analysts are not impartial observers of financial markets who judiciously issue unbiased forecasts that inform investors and result in an efficient allocation of scarce resources. Instead, there is voluminous evidence that brokers are prone to overconfidence bias and optimism that are, to some extent, caused by conflicts of interest. In contrast to the arguments of Jensen and Meckling (1976), Doukas *et al.* (2005) find that these biases result in greater analyst coverage being associated with increased divergence of prices from their fundamental values.

Furthermore, there is evidence that companies manipulate investors' expectations by guiding analysts towards their expected earnings and ensuring that they meet or marginally beat such forecasts through earnings manipulation. Overall, the evidence on the role of brokers in financial markets is mixed. The subsequent sections examine the veracity and impact of brokers' output, with particular focus on whether the conflicts of interest and cognitive biases prevent brokers from conveying the true economic value of their information to the public.

4.3 The accuracy of analysts' forecasts

Research on the effects of brokers' recommendations has primarily focussed on two key questions. First, do brokers' recommendations have predictive power (a test of the strong-form leg of the EMH) and second, do they induce trading activity? The answers to these questions are of great importance to understanding the source of any profits to contrarian or strength rule strategies. This section examines the information content of analysts' forecasts and recommendations; while section 4.4 discusses the volume and price impact of brokers' recommendations.

Grossman and Stiglitz (1980) assert that market prices cannot be perfectly efficient as this would result in information gatherers having no incentive to undertake their costly activities. However, this need not imply that analysts' forecasts are of economic value as sell-side analysts are compensated via alternative channels, such as underwriting fees and commissions. In contrast, the recommendations of buy-side analysts must be of economic value in order to justify their expense. Accordingly, the principal set of profitable recommendations may be the one that is not issued to the general investing public[48].

The output of analysts generally appears in four forms and research has focussed on the accuracy and impact of each of these four categories. The three most commonly analysed measures are target prices, EPS forecasts, and the overall recommendation category (buy, sell, hold, etc.). A fourth, often overlooked, measure is the written justification of an analyst's advice. Empirical work has focussed on the information content of the absolute level and revisions of each of the above four measures.

There is much debate surrounding the value of investment advice issued by financial professionals such as brokers, analysts, and money managers. Cowles (1933) was the first to examine the accuracy of analysts' recommendations, finding that, on average, the recommendations of financial services firms, *Wall Street Journal* editorials, and other 'experts' underperformed the market. Furthermore, the returns of superior analysts were probably due to chance[49]. Cowles (1944) confirms these findings when extending the dataset for 11 of the 14 financial publications examined in the original study.

The profitability of recommendations collected from the institutional research departments of brokerage firms was first examined by Diefenbach (1972), who found that, on aggregate, there was little value in following such recommendations. Studies such as Logue and Tuttle (1973), Fitzgerald (1975), and Bidwell (1977) reach similar conclusions. Colker (1963)

[48] Buy-side analysts work for private equity, pension, or mutual funds and issue their recommendations exclusively to their money managers. Their performance is evaluated purely on the basis of the profitability of their recommendations as they do not generate fees.

[49] However, Michaely and Womack (2004) assert that the period of study in Cowles' work was biased at it included the stock market crash of 1929.

concludes that recommendations (published in the *Wall Street Journal's* 'Market Views-Analysis') only marginally outperform the market and that either professional securities dealers could not accurately quantify their superior information or their best projections do not become public knowledge. In contrast, Bjerring *et al*. (1983) find that investors following the recommendations of Canadian brokers could make significant abnormal returns, even after allowing for transaction costs.

Crichfield *et al.* (1978) find that there is no systematic bias in the earnings forecasts of analysts[50]. It should be noted that accurate earnings forecasts need not necessarily facilitate profitable recommendations as there may be a disconnect between earnings and share prices[51]. Bradshaw (2004) shows that analysts' recommendations are associated with heuristic models more than present values; thereby broadening the disconnect between earnings forecasts and share prices. Bradshaw (2004) concludes that investors can outperform analysts' recommendations by discounting the earnings forecasts of analysts using simple present value models. Dreman and Berry (1995b) assess 66,100 consensus earnings estimates and document significant forecast errors on average.

In contrast, Ertimur *et al.* (2007) show that analysts with low conflicts of interest are capable of translating accurate forecasts into profitable buy recommendations by isolating cases where earnings are value relevant. Loh and Mian (2006) similarly document a positive correlation between accurate earnings forecasts and profitable recommendations.

Cragg and Malkiel (1968) and Elton and Gruber (1972) find that analysts' forecasts fail to outperform those of time series and regression models. This would suggest that security analysis does not add value and thus the resources committed to such research constitute an economic loss. However, Brown and Rozeff (1978) question the experimental and parametric techniques used in these studies and find that analysts' forecasts outperform time-series models. Similarly, Hussain (1996), Patz (1989), and Capstaff *et al.* (1995), show that

[50] For further early evidence documenting the information content of analysts' earnings forecasts and recommendations see, *inter alios*, Cheney (1969); Lloyd-Davies and Canes (1978); and Elton *et al.* (1986).
[51] See, for example, Barth *et al.* (1998).

UK brokers outperform naïve forecasting models for forecasting periods of shorter than three, 12, and 16 months ahead, respectively.

Aitken *et al.* (2000) find that recommending brokers do have stock picking ability in that buy and sell recommendations result in abnormal returns in the predicted directions. Furthermore, there is a positive relationship between the strength of the recommendation and the size of the abnormal return. Interestingly, returns in the pre-recommendation period are higher than those after the announcement. This implies that brokers' timing may not be fully accurate, brokers may be reactive rather than proactive, or that there is some type of leakage to certain clients (or front-running). Alternatively, some recommendations may be based on technical analysis and by the time the recommendation is released the trend may have largely exhausted itself. Groth *et al.* (1979) also find that the excess returns prior to a positive recommendation are much larger than those that could have been earned after the recommendation.

This implies that recommendations are somewhat dated by the time of issue. Accordingly, if investors act as prescribed an overreaction may be expected to occur whereby the share price is driven above its fundamental value. As explained earlier, a reversal may follow. Aitken *et al.* (2000) confirm this to a certain degree by finding a partial reversal subsequent to the recommendation day. However, the authors find that sell recommendations have a more permanent impact on prices, suggesting that analysts may engage in momentum trading (or recommending) for past winners but not for losers.

Dugar and Nathan (1995) and Clarke *et al*. (2006) find that the returns to following the advice of affiliated brokers do not differ significantly from those to other analysts. Dugar and Nathan (1995) find that market participants are cognisant of potential conflicts of interest and utilise the output of non-affiliated analysts to a greater degree in forming their earnings expectations. However, differences in trading volumes to the advice of each type of analyst are insignificant. Clarke *et al*. (2006) also find that market reaction does not depend on affiliation.

Dimson and Marsh (1984) find that the forecasts of institutional (buy-side) analysts are disseminated quicker than those of other analysts. This is to be expected as institutional analysts participate in trading and thus their views should be reflected in stock prices more instantly. Accordingly, investors must react in a rapid fashion in order to take advantage of any profits.

This is supported by Womack (1996), who finds that the majority of the price impacts to buy recommendations are observed in the three-day period surrounding the recommendation. However, abnormal returns persist for up to six months for sell recommendations. Mean reversion is observed for buy recommendations but not for sell recommendations, suggesting that buy recommendations are overly-optimistic and contribute to continuation followed by reversal. Womack (1996) views the greater returns to sell recommendations as a reward to compensate for the additional 'costs' involved in issuing negative recommendations (as will be discussed in section 4.5).

Naturally, not all analysts are created equally and there is evidence that the recommendations of certain groups of analysts yield positive abnormal returns. Stickel (1992) shows that the forecasts of the *Institutional Investor* All-American Research Team[52] are more accurate, less biased, more frequent, and their forecast revisions have a greater impact on prices, than the forecasts of other analysts.

Desai *et al.* (2000) find that stocks recommended by *Wall Street Journal* All-Star analysts outperform the market, while Sinha *et al.* (1997) find evidence of superior performance for analysts who were marked out as superior in the previous period. There is also extensive evidence of the investment value contained in the recommendations published in the 'Heard on the Street' and 'Dartboard' columns published in the *Wall Street Journal*[53]. Similarly, Mikhail *et al.* (2004) find that an analyst's superior performance tends to continue from one

[52] Each year the *Institutional Investor* asks approximately 2,000 money managers to evaluate analysts based on four criteria: stock picking, earnings forecasts, written reports, and overall service. Being one of the select 'All-Americans' can be viewed as a proxy for reputation and pay, as membership of this list is one of the three main criteria for determining pay (Stickel, 1992).

[53] See, *inter alios*, Lloyd-Davies and Canes (1978); Beneish (1991); and Bauman *et al.* (1995).

period to the next. In contrast, Conroy *et al.* (1997) find that there is no significant link between a broker's forecast errors in subsequent years, while Elton *et al.* (1986) and O'Brien (1990) find no evidence of significant differences in the forecast accuracy of individual analysts.

Hendricks *et al.* (1993) provide evidence of short-run persistence in mutual fund performance, suggesting that some fund managers have 'hot hands'. Performance continuation is more pronounced for underperforming funds ('icy hands'). Goetzmann and Ibbotson (1994) also provide evidence of persistence in the performance of fund managers. However, Carhart (1997) argues that the results of Hendricks *et al.* (1993) can be explained by investment fees, transaction costs, risk, and one-year momentum in returns. Carhart (1997) concludes that there is no evidence consistent with the existence of skilled or informed mutual fund portfolio managers[54].

Fletcher and Forbes (2002) further highlight the importance of using Carhart's four-factor model in order to separate a mutual fund's stock picking ability from its ability to profit from momentum in returns. The authors document evidence of persistence in mutual fund performance in the UK when using traditional return-generating models, such as the CAPM. However, there is also evidence of continuation in the performance of portfolios based on past performance and mutual fund persistence disappears when Carhart's model incorporating momentum is employed.

Ferreira and Smith (2003) analyse the information content of the recommendations of panellists on the television show 'Wall $treet Week with Louis Rukeyser'. They find statistically significant abnormal returns of 0.65% in the first day after the show was aired. Such recommendations appear to have significant information content as recommended stocks outperform industry and size matched stocks in the subsequent eight quarters. However, even the recommendations of top-performing analysts often fail to generate excess returns after accounting for transaction costs. Desai and Jain (1995) show that the performance of 'superstar' money managers at the *Barron's Annual Roundtable* is

[54] Carhart (1997) does, however, present evidence of momentum in the performance of underperforming funds.

insufficient to cover transaction costs[55]. The authors find that the market response to sell recommendations is considerably stronger than that for buy recommendations.

Clement (1999) and Jacob *et al.* (1999) find that forecast accuracy is greatest for experienced analysts who work for large brokerage houses and focus on a relatively small number of firms and industries. Sorescu and Subrahmanyam (2006) provide confirming evidence of the superior forecasting ability of analysts of large and prestigious banks respectively. On the other hand, Richards (1976) finds insignificant cross-sectional variation in the forecasting ability of analysts and thus suggests that, *ceteris paribus,* investors should source the least expensive analyst.

The majority of the above studies examine the recommendation *levels*. One may expect that there should be a more pronounced market response to *changes* in an analyst's recommendation level for a covered firm, particularly for downgrades. The paltry number of recommendation categories used by analysts combined with their reluctance to downgrade suggests that it must take significant information to elicit a downgrade. Ho and Harris (1998) confirm that downgrades elicit a greater price response.

Elton *et al.* (1986) find that brokers' upgrades and downgrades contain significant information and the abnormal returns to trading on these revisions persist for two months after the revision. There is abundant evidence of the information content of revisions to earnings forecasts (for example, Lys and Sohn, 1990; Mikhail *et al*., 1997), recommendation levels (Azzi and Bird, 2005; Chan *et al.*, 2006), and target prices (Brav and Lehavy, 2003; Bradshaw, 2002).

Givoly and Lakonishok (1979) show that analysts' forecast revisions are informative. Notably, the authors show that the market responds in a delayed fashion, causing post-revision announcement drift. Dische (2002) similarly shows that prices drift in the direction of a forecast revision in a predictable manner and the strength of the market's reaction is

[55] Barron's Annual Roundtable is a gathering of top-performing money managers and analysts organised by the American financial newspaper *Barron*.

positively correlated to the level of analyst agreement. It takes up to six months for the majority of the information to be incorporated into share prices. Thus, there is a negative relationship between momentum returns and analyst dispersion.

This finding is in stark contrast with the predictions of the models of Daniel *et al.* (1998) and Hong and Stein (1999), which suggest that momentum returns should be greater for high dispersion firms due to their higher level of information asymmetries. Instead, the evidence is consistent with the conservatism model postulated by Barberis *et al*. (1998), which posits that investors are slow to update their beliefs as they underweight new information. Notably, Mear and Firth (1987) find that surveyed financial analysts overestimate (underestimate) the weight placed on minor (major) cues. This can be viewed as early evidence of a conservatism bias that may lead to underreaction and concomitantly to momentum in stock returns.

This section has outlined the mixed evidence on the accuracy of brokers' forecasts and some evidence on the linkages between the output of brokers and the two anomalies under review in this thesis. The next section provides further evidence of these linkages by examining the impact of brokers' prognostications.

4.4 Impact of brokers' recommendations

The output of brokers can have significant volume and price impacts and is thus central to understanding the information and price efficiencies of financial markets. This is particularly apposite when investors do not react immediately to the recommendations of analysts. Consider the situation where a leading broker issues a strong buy recommendation on a stock. If some investors react more slowly than others then a strength rule strategy may prove to be profitable as a result of underreaction. However, if the recommendation proves to be over-optimistic then a reversal may be observed over the longer term. Thus, brokers may contribute to the parabolic pattern in prices that facilitate profitable short-term strength rule and long-term contrarian investment strategies.

The buying and selling actions of the brokerage firm's proprietary traders is also of vital importance. It is normal for a considerable period of time to elapse before a broker's recommendation is made public. If the brokerage firm trades before making the buy recommendation public then a large part of the advice may be redundant. The stock price may rise beyond its fundamental value and subsequently reverse if a sufficient number of investors act on such advice. Such information leakages and front-running may occur despite the existence of Chinese Walls and may explain the evidence discussed in section 4.3 that abnormal returns are highest in the pre-recommendation phase.

The above parabolic pattern of returns may also be explained with reference to speculative bubbles or self-fulfilling prophecies that may be accentuated by herding and thought contagion. If a broker recommends a stock (without justification) and some investors buy the stock, more investors may jump on the bandwagon causing a speculative bubble. This bubble may eventually burst with stocks returning to their fundamental values. Jegadeesh *et al*. (2004) show that analysts often focus on stocks with high positive price momentum, while Welsh (2000) finds that herding is common among analysts. These issues are examined in greater detail in sections 4.7 and 4.8, respectively.

The link between analysts' output and momentum is strengthened by the vast archival evidence that brokers are much more likely to issue 'buy' recommendations than advice to sell. Rajan and Servaes (1997) and Michaely and Womack (2004) find that the ratio of buy-to-sell recommendations was approximately 10-to-1 up to the early 1990s, but became even more weighted towards buy recommendations thereafter. Barber *et al*. (2006) state that by mid-2000 the percentage of buy recommendations rose to 74% of total outstanding recommendations, dwarfing the 2% of sell recommendations. Furthermore, analysts' reluctance to revise their forecasts (Erturk, 2006) results in prolonged runs of consecutive buy recommendations. If investors interpret such recommendations sequentially (or believe that they constitute new information), share prices will exhibit momentum.

Aitken *et al.* (2000) find that recommendations cause increased trading and more business for the advice-issuing brokers. Buy recommendations are found to affect trading in a more pronounced manner than sell recommendations. Womack (1996) finds that stocks typically appreciate by two per cent or more on the day of buy recommendation initiations; while trading volume doubles. Michaely and Womack (2004) show that trading increases in the pre-recommendation stage but is not as pronounced as the post-recommendation increase. Such post-recommendation increases in trading activity can persist for a significant number of days suggesting that some investors do not react instantaneously. This may point to the profitability of a short-term strength rule.

Stickel (1992) and Clement and Tse (2005) show that the market responds to a greater degree to the forecasts of top-rated analysts and those employed by large banks respectively. Bonner *et al.* (2007) and Sorescu and Subrahmanyam (2006) show that the market reacts more acutely to the forecasts of analysts of high repute. Gleason and Lee (2003) show that the market responds more rapidly and completely to the forecast revisions of high-profile analysts.

Using an extensive sample from Zacks Investment database, Stickel (1995) shows that buy and sell recommendations (and revisions) have a significant short-run impact on share prices in the prescribed direction. The magnitude of the price impact is positively correlated with the strength of the recommendation, the magnitude of change, the presence of contemporaneous earnings forecast revisions, the reputation of the analyst, and the size and marketing ability of the brokerage house and is negatively correlated with firm size. Similarly, Jegadeesh and Kim (2006) provide evidence of significant abnormal volume on the day of upgrades and downgrades, as well as the day before and after such recommendation changes.

Asquith *et al.* (2005) argue that the traditional discrete stock recommendation categories (strong buy, buy, hold, sell, strong sell) are too limited; a problem accentuated by the findings that analysts are reluctant to use the two negative ratings. Asquith *et al.* (2005) show that only 0.5% of recommendations are sell or strong sell; possibly due to the underwriting relationship between firms and brokerage houses observed in more than half of the cases reviewed.

Asquith *et al.* (2005) incorporate gradations in the analysts' price targets as well as the contents of analyst reports in order to get a more accurate picture of the information content of analyst reports. The authors find that changes in earnings forecasts, stock recommendations, and price targets all provide independent information signals to capital markets. Furthermore, stronger justifications given in an analyst's report result in a more pronounced market reaction. Finally, investors tend to react more to an analyst report when it is a downgrade, perhaps because the relatively high frequency of upgrades and analysts' conflict of interest lead investors to be sceptical of positive recommendations.

Kerl and Walter (2008) also show that there is valuable information contained in the earnings forecast and target price revisions of German analysts. Interestingly, they find that there is independent information contained in the justifications of such published advice contained in the written reports of such analysts. The market reacts most significantly to the written justifications and investors do not account for any relationship between a brokerage firm and the company that it covers.

Michaely and Womack (2004) explain the dynamics associated with the dissemination of brokers' recommendations prior to Regulation Fair Disclosure (Reg FD). Recommendations can be classed as urgent, timely, or routine. It is the mechanics of the delivery of routine brokers' reports that is of most importance to the analysis of the strength rule and contrarian investment strategies. Urgent information is immediately disseminated to relevant interested parties; first to the sales-force of the brokerage firm; and subsequently via the sales-force to clients. Alternatively, the broker may contact important customers directly once the salespeople have been informed. Timely information is customarily disseminated to large buy-side traders and portfolio managers via morning conference calls before markets open.

Thus, both of the above sets of information are made available relatively quickly and to a relatively large amount of investors. Therefore, it can be expected that investors will react in a timely fashion. An agency, such as *Reuters*, may also transmit any recommendations or reports, thus in theory further unifying and accelerating the market's response. For routine reports the time-frame involved in the dissemination of information is somewhat more elongated. Large clients may receive reports sooner, whereas smaller clients may have to wait for such reports to arrive in the mail. Thus, the market's reaction to a routine recommendation (or update) may occur consecutively rather than contemporaneously, thereby leading to a chain reaction and drift.

Furthermore, Malmendier and Shanthikumar (2007) find that small investors react to the reiteration of previously released buy and strong buy recommendations. This may explain why share prices overshoot their fundamental values. Similarly, Syed *et al.* (1989) find that the publication of recommendations in the *Wall Street Journal*'s 'Heard on the Street' column elicits significant market reactions, even in cases where such recommendations are leaked prior to publication.

Han and Suk (1996) examine the trading impact of the release of analyst recommendations in *Barron's* 'Research Reports' column. Such advice is previously released by investment firms and is thus effectively old information by the time it appears in *Barron's* column. However, investors appear to trade as if constitutes new information and this causes momentum, as a similar response was registered when the information was first released. The fact that returns reverse within five trading days of the initial recommendation is consistent with investors reacting in a delayed fashion and trading on old information.

Palmon *et al.* (2009) find that the buy recommendations of columnists in *Business Week*, *Forbes* and *Fortune* magazines are associated with increased share prices prior to, and on, the day of publication. However, it would not be possible for investors to make consistent long-term abnormal returns by following such recommendations.

Barber and Loeffler (1993) find evidence of abnormal returns for stocks recommended in the *Wall Street Journal's* 'Dartboard' column. They argue that such recommendations constitute second-hand information, consistent with the delayed-response hypothesis. However, Beneish (1991) argues that such information is, in many cases, first-hand information as analysts have an incentive to publish information via the media before revealing it to their clients in order to establish their reputation. Beneish (1991) argues that the positive returns in the days prior to publication are caused by insiders trading on information before it is published, rather than investors trading on publicly released information.

The delayed reaction of investors to the output of analysts constitutes only one of the two potential strains on the diffusion process between news and prices. Analysts may also delay updating their recommendations in light of news. Zhang (2008) finds that analysts' responsiveness to earnings announcements varies significantly. Analysts that respond earlier tend to make more accurate forecasts, mitigating the extent of the PEAD. Zhang (2008) concludes that the results are consistent with the delayed-response hypothesis, as argued by Bernard and Thomas (1989).

Specifically, Zhang (2008) finds that 44% of sell-side security analysts issue forecast revisions within two trading days of an earnings announcement, with the remaining analysts taking an average of 34 days to revise their forecasts. The absolute forecast errors of the non-responsive analysts are significantly larger than those of the responsive analysts, suggesting that the earnings announcements contain new information. Zhang (2008) finds that this underreaction, as measured by serial correlation in forecast errors, is twice that of the responsive analysts. Finally, Zhang (2008) finds that the PEAD is approximately one-third lower for firms followed by responsive analysts only than for those followed by non-responsive analysts alone. Jegadeesh and Livnat (2006) also find that analysts are slow to incorporate the information in revenue and earnings surprises into their earnings forecasts, taking up to six months to do so.

Unsurprisingly, Michaely and Womack (2004) show that the returns to be made from following analysts' recommendations are negatively correlated with investors' reaction time. However, the window of opportunity is not restrictively narrow. Share prices are found to drift for a number of weeks or months. It is a matter of debate whether markets are thus reacting in an inefficient manner to the news incorporated in these recommendations or whether brokers are manipulating stock prices by temporarily pushing them away from their fundamental values through issuing self-fulfilling prophesies. Jegadeesh and Kim (2006) similarly show that stock prices drift for two to six months after recommendations are issued.

Brown *et al.* (2007) find that the share-price response to initiating recommendations by Australian brokers is greater than that for continuing recommendations, especially for the more negative recommendation categories. The response to positive initiating recommendations is more muted, perhaps due to investors discounting such recommendations in light of potential conflicts of interest or bandwagon effects. In contrast, Chan *et al.* (2006) find no significant difference between returns to initiating and continuing recommendations of Australian brokers.

In the US, Peterson (1987), Womack (1996), and McNichols and O'Brien (1997) show that initiating recommendations produce positive abnormal stock returns at the time that the recommendation is released. Irvine (2003) shows that the price impact of an initiation is one percentage point greater than that of a continuing recommendation. Bauman *et al.* (1995) and Lloyd-Davies and Canes (1978) find significant announcement-date returns for recommendations made in the *Wall Street Journal*'s 'Heard on the Street' column. Bauman *et al.* (1995) show that investors appear to overreact to such recommendations as returns reverse over the subsequent days. Pre-recommendation returns are significantly positive (negative) for buy (sell) recommendations. Similarly, Lin *et al.* (2009) show that the information contained in analysts' recommendations published in the printed press in Taiwan is leaked prior to publication as the major price response occurs prior to the publication date.

Busse and Green (2002) provide evidence of the immediacy with which analysts' forecasts are factored into share prices. The authors show that prices respond within seconds of being positively recommended on CNBC's Morning and Midday Call reports[56]. Trading volume and intensity increase and positive reports are fully incorporated within one minute. Traders must respond within 15 seconds in order to make small but significant profits. Similarly, Green (2006) shows that investors can generate two-day returns in excess of one per cent if they have early access to recommendation revisions. Such opportunities persist for two hours following the pre-market release of the upgrade or downgrade to clients.

[56] There is a larger but more gradual response to sell recommendations, possibly due to short-selling constraints (Busse and Green, 2002).

It thus appears that brokerage houses provide valuable information to their clients, the majority of which is redundant by the time it reaches remaining market participants. One can surmise that if such recommendations are reprinted at a later date, any resulting trades would causes an overreaction as the information content has already been efficiently incorporated into share prices.

In summary, it is clear that brokers' recommendations and forecasts have a significant impact on share prices and volume and can thus explain the two anomalies under review. The next section examines whether this link is strengthened by potential conflicts of interest on the part of brokers and covered companies.

4.5 Conflicts of interest

It is important to note that any evidence showing that analysts' recommendations are of insignificant economic value does not necessarily imply that analysts do not possess superior information. Anecdotal and academic evidence suggests that analysts' conflicts of interest often prevent them from communicating the true content of their information to the public.

This section focuses predominantly on the behaviour of sell-side analysts, who by definition have more potential conflicts of interest, as their compensation is generally based on commission and underwriting fees generated rather than fund performance (as is the case for buy-side analysts)[57]. It also examines the incentives of companies to manage earnings and guide analysts and the concomitant earnings-guidance game.

4.5.1 Causes of conflicts of interest

Analysts are conflicted between the desire for accuracy and the incentive-driven need to produce optimistic forecasts. Empirical and anecdotal evidence suggests that the financial and career incentives of the latter dominate the reputational and financial incentives of the

[57] The clients of brokerage firms do not generally pay directly for investment advice but pay indirectly in the form of commissions on the trades that are triggered by such advice (Kerl and Walter, 2008).

former. The trade-off is particularly pertinent when an analyst forms a negative view on the prospects of a firm but the need to generate underwriting fees and maintain access to the covered firm's non-public information clouds the analyst's thinking. It is also more germane when there is greater uncertainly over the future earnings of a firm, thereby increasing the value of non-public information.

Lim (2001) models this trade off and shows that utility-maximising behaviour involves the issuance of over-optimistic forecasts. Paradoxically, analysts can improve long-term forecasting accuracy by deliberately biasing forecasts upwards. The marginal (short-term) error in doing so is more than offset by the access to non-public information that it facilitates. Thus, the trade-off between accuracy and reward may be more apparent than real. Lim (2001) confirm the model's predictions empirically[58].

Conflicts of interests arise from three main sources. First, analysts who work for investment houses aim to please clients by issuing favourable recommendations due to the pressure to generate investment banking fee revenue (from equity offerings and M&A deals)[59]. Kolasinski and Kothari (2004) label this the 'bribery' hypothesis. Second, there is pressure to generate brokerage commissions and it is argued that positive research/recommendations stimulate trading (the 'underwriting' or 'marketing' hypothesis')[60]. Finally, analysts may want to keep the management of covered companies satisfied by issuing favourable recommendations in order to ensure they have access to senior management and to timely information (the 'information hypothesis')[61].

The 'bribery' hypothesis is supported by Hayward and Boeker (1998), who show that analysts working for investment banks are more optimistic about the prospects of stocks owned by their clients than other analysts. This optimism is more pronounced for large

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[58] This suggests that the documented evidence of a positive association between analyst experience and accuracy may be attributable to greater access to information as a reward for compliant analysts, as opposed to learning on the part of such analysts.
[59] See Michaely and Womack (1999); Carleton *et al.* (1998); and Dugar and Nathan (1995).
[60] See Cowen *et al.* (2006); Irvine (2004); and Jackson (2005).
[61] See Lim (2001); Das *et al.* (1998); and Francis and Philbrick (1993).

clients, who are more likely to engage in large capital offerings and M&A deals, and increases as the date of such deals approaches.

Michaely and Womack (1999) show that the buy recommendations of analysts covering firms whose Initial Public Offering (IPO) was managed by the analyst's investment bank underperform those of unaffiliated brokers. In the long-run, underwriting analysts underperform their unaffiliated counterparts by more than 50%. However, the market fails to fully discount this underwriting bias as the authors document short-run excess returns of 2.7% for underwriter analyst recommendations; compared to 4.4% for unaffiliated analysts.

Michaely and Womack (1999) show that the poor performance of underwriting analysts is not due to ability, as such analysts are more accurate when evaluating the prospects of firms for whom they were not the lead underwriter. Conflicts of interest appear to overwhelm underwriting analysts' informational advantage, which should arise from information gathered during the due-diligence process prior to the IPO.

In a theoretical setting, Hayes (1998) finds that analysts have greater commission-driven incentives to collect information on firms that they expect to perform well, as argued by McNichols and O'Brien (1997). Short-sale constraints may further incentivise analysts to issue buy recommendations and generally focus on stocks that are expected to perform well[62]. Hayes (1998) posits that analysts' earnings forecasts for such firms should be accurate as their optimism is justified.

Irvine (2004) shows that firms can generate greater brokerage commissions by optimistically biasing their forecasts, as buy recommendations stimulate trading to the greatest extent. Dorfman (1991) notes that analysts' bonuses are often tied to the commissions that their recommendations generate for the brokerage firm. Brennan and Hughes (1991) and Alford and Berger (1999) show that analysts tend to follow firms that generate greater brokerage commissions, such as those that announce stock splits. Chung (2000) also provides evidence

[62] If short-sales are prohibited or excessively costly, sell recommendations can only generate commission from the current holders of a stock. On the other hand, buy recommendations can generate commissions from a wider pool of investors.

consistent with the marketing hypothesis of analyst following, as analysts are attracted to high-quality firms in response to investors' preference for such firms.

Chan *et al.* (2007) assert that analysts are now cheerleaders for the firms they cover, rather than impartial providers of information. The authors argue that the correlation between the surge in non-negative earnings surprises in the 1990s and the increase in underwriting activity is not coincidental and can perhaps be explained by the conflicts of interest that analysts face. Chan *et al.* (2007) show that non-negative earnings surprises are more likely in growth firms as opposed to value firms, as the former are more likely to be involved in mergers and acquisitions and need to raise fresh capital. Furthermore, earnings surprises tend to display less positive bias in countries with weaker links between investment banking and analyst research.

The financial press is replete with anecdotal evidence documenting the perils of issuing unfavourable reports on a firm. Chen and Matsumoto (2006) summarise a number of such reports of firms closing the lines of communication to analysts following downgrades[63]. A *Reuters* survey indicates that 88% of analysts fear negative consequences from the companies they cover if they were to issue negative opinions on the companies (NIRI, 2003b).

Erturk (2006) argues that analysts' reluctance to revise their earnings forecasts downwards due to conflicts of interest leads to market underreaction to bad news. Erturk (2006) finds that a strategy of buying low-dispersion stocks and short selling high-dispersion stocks earns 0.75% in one month (but monotonically decreases with longer holding periods). O'Brien *et al*. (2005) provide supportive evidence of this thesis by showing that analysts affiliated with underwriter banks are slower to downgrade and quicker to upgrade than other analysts.

Conrad *et al.* (2006) find that analysts are reluctant to downgrade recommendations and show that there is a greater chance of an analyst upgrading a stock when their brokerage house has an investment banking relationship with the company under review. Elton *et al.* (1986),

[63] For further anecdotal evidence see, for example, Doukas *et al*. (2005); Hayward and Boeker (1998); and Michaely and Womack (1996 and 1999).

provides cogent evidence of the inertia in recommendations, reporting that only approximately 12% of a sample of 10,000 recommendations are revised to a different level.

4.5.2 Earnings guidance and management

In addition to inducing trading and following momentum strategies, analysts can have a significant impact on stock prices via earnings surprises. Lopez and Rees (2002) find that the market premium for meeting forecasts is less than the market penalty for missing forecasts. Managers' incentives to reach or surpass earnings targets are also driven by bonuses, stakeholder motivations, bond covenants, career and reputational concerns, and the use of elevated share prices as a method of defending against hostile takeovers.

It is thus unsurprising that there is abundant evidence that firms go to extensive lengths to avoid negative earnings shocks[64]. Companies can avoid negative earnings surprises through earnings management or via guidance management. The former involves the company taking actions to alter their reported earnings in order to meet or beat an earnings forecast, while the latter involves manipulating the forecast in order to align it with the expected actual earnings. Matsumoto (2002) finds that firms manage their earnings upwards and guide analysts' forecasts downwards in order to avoid negative earnings surprises.

Earnings management is used to avoid negative earnings surprises and smooth earnings[65]. If earnings are artificially prevented from following their naturally erratic path in favour of a smooth but increasing time-series of earnings, then a clear link exists between earnings management and long-term momentum returns. If there is a strong relationship between reported earnings and share prices then, *ceteris paribus*, steadily increasing earnings will result in positive serial correlation in share prices. Any subsequent unwinding of earnings management may result in reversal.

[64] See, for example, Burgstahler and Dichev (1997).

[65] Graham *et al.* (2005) find that 96.9% of surveyed Chief Financial Officers (CFOs) have a preference for a smooth earnings path as the market values predictable earnings.

The manipulation of accounting information is not the only method that firms use to meet earnings forecasts. The myopic quest to meet earnings expectations can distract a firm from its long-term objectives and result in sub-optimal behaviour. Graham *et al.* (2005) find that 78% of Chief Financial Officers (CFOs) admit to sacrificing long-term value in order to smooth earnings. Managers prefer to take actions that may have negative long-term consequences, such as delaying maintenance or advertising expenditure or sacrificing positive NPV projects, than making within-GAAP accounting choices to manage earnings, such as accrual management.

The second method of avoiding negative earnings surprises involves manipulating the market's forecasted earnings figure in order to increase the company's chances of meeting or beating such a projection. This method is often referred to as 'guidance management' or 'expectations management'. The 'earnings guidance game' involves analysts issuing an optimistic forecast for firm and then 'walking down' their prediction to a more achievable (pessimistic) level, due in part to guidance from managers (Richardson *et al.*, 2004).

Graham *et al.* (2005) find that more than 80% of surveyed CFOs admit to guiding analysts to some degree. CFOs state that they guide analysts in order to reduce forecast dispersion and often guide analysts to a figure below the internally generated target in order to increase the probability of beating such a forecast. One CFO described their guidance policy as "under-promise and over-deliver" (Graham *et al.* 2005, p.42). Furthermore, survey evidence suggests that earnings and guidance management are pervasive. In the US, a National Investor Relations Institute (NIRI) survey finds that 77% of firms surveyed indicate that they provide guidance to analysts and 98% said they believe analysts want guidance (NIRI, 2003a).

In the absence of cooperation from analysts, companies can manage earnings expectations by talking down earnings as the announcement date approaches. The walking down of earnings, either via analysts or directly by the company, will result in serial correlation in share prices, thereby facilitating the profitability of a momentum strategy.

4.5.3 Optimism/pessimism

The conflicts of interest and earnings-management game outlined above tend to manifest themselves in initially optimistic forecasts followed by downward revisions to a pessimistic level as the earnings announcement date approaches. This sub-section examines the evidence relating to analyst optimism in more detail.

Cowles (1944) was the first to cogently show that analysts' forecasts have a tendency to be over-optimistic. Cowles (1944) shows that bullish recommendations outnumber bearish forecasts by a factor of four, despite more than half of the period under review being characterised by bear market conditions and the observation that stocks lost approximately one-third of their value on average.

Brav and Lehavy (2003) find that the average target price for one year hence is 28% higher than the current market price. This suggests an excessive level of optimism as the dataset used covers an extensive range of firms; thus expected returns should closely mirror that of a market index. Chopra (1998) finds that Wall Street analysts forecast average EPS growth of 17.7%, which is more than twice the actual ensuing growth rate. Analysts consistently 'walk down' forecasts throughout the year as a result of their overoptimistic initial estimates.

Jegadeesh *et al.* (2004) show that sell recommendations account for less than five per cent of US analysts' recommendations between 1985 and 1998. Jegadeesh and Kim (2006) find that the equivalent figure for the period 1993-2001 is 3.3%[66]. Lloyd-Davies and Canes (1978), Stickel (1995), Ho and Harris (1998) and Womack (1996) find buy-to-sell ratios of 3.2:1, 4.6:1, 5.2:1, and 7:1, respectively for the US. Elton *et al.* (1986) examine 10,000 brokerage recommendations and find a buy-to-sell ratio of 3.5:1, with the most negative rating being used in only approximately two per cent of cases.

There has been a significant decrease in the predominance of buy recommendations in the US since the introduction of NASD Rule 2711 (see section 4.5.4). However, Irish brokers are

[66] This contrasts with an average proportion of sells of 15.3% for the G7 nations excluding the US.

not covered by this rule and Ryan (2006) reports a ratio of 7.2:1 for Irish brokerage houses[67]. Moshirian *et al.* (2009) document a ratio of positive-to-negative recommendations of approximately 1.4:1 for a sample of emerging markets and show that the proportion of sell recommendations issued by analysts in such markets is considerably less than their counterparts in developed markets.

Excessive optimism can be explained by the conflicts of interest outlined in section 4.5. The 'information hypothesis' states that as the forecasting task becomes more complex, analysts have a greater incentive to bias their forecasts upwards in order maintain access to information of the covered company as the marginal benefit of such information increases (Das *et al.*, 1998).

Similarly, Ke and Yu (2006) show that analysts that engage in the earnings-guidance game with covered firms produce more accurate forecasts and are less likely to lose their job. This finding is particularly strong for firms with more uncertain earnings and heavier insider selling. The results do not vary significantly for affiliated and unaffiliated analysts, thereby suggesting that it is information, rather than brokerage fees, that encourage analysts to compromise their forecasts.

Ivković and Jegadeesh (2004) find no evidence that analysts possess a superior ability to process publicly available information as their revisions are least informative in the week following earnings announcements. In contrast, the authors document a significant increase in the information content of positive revisions in the week before earnings announcements. This suggests that any superior forecasting ability may be attributable to access to private information as the covered company's accounts would be completed, but not publicly released, in the period immediately prior to the earnings announcement.

Optimistic forecasts may also stem from analysts' desire to generate trading and underwriting fees. Lin and McNichols (1998) find that stock recommendations and earnings forecasts tend

[67] This thesis performs an out-of-sample test of Ryan's findings using the updated time period 2007-10 and focuses on the differences between brokers working for Irish and non-Irish brokerage houses.

to be more favourable when an analyst is affiliated with underwriters, while Carleton *et al.* (1998) and Hussain (1996) show that brokerage firms tend to issue more optimistic recommendations than their non-brokerage counterparts. Dechow *et al.* (2000) show that the forecasts of affiliated sell-side analysts at the time of equity offerings are over-optimistic and report a positive relationship between the level of optimism and the fees paid to the brokerage house by the issuing company.

Jackson (2005) shows that optimistic analysts in Australia generate higher trading volumes (and thus commissions), giving them an incentive to bias forecasts upwards. The power of such incentives is partially reduced by long-term reputational concerns. Jackson (2005) shows that analysts with better reputations tend to generate more commissions for their brokerage firms. Thus, there may be incentives for analysts to forego the short-term incentive of increased commissions at the beginning of their careers in order to build up their reputation, which can be used to generate larger commissions in the long run.

Bartov *et al.* (2002) find that the proportion of companies meeting or beating analysts' estimates has increased considerably in recent years. This may seem inconsistent with the prevalence of optimistic forecasts. However, the two are not mutually exclusive due to the dynamics of the earnings-guidance game. Actual earnings are typically compared with the most recent earnings forecast. Therefore, it is possible for analysts to issue optimistic forecasts on average and walk down forecasts to a beatable level, thereby explaining the co-existence of optimistic forecasts and non-negative earnings surprises[68].

Beckers *et al.* (2004) examine how the optimism bias of consensus forecasts of European brokers is affected by a number of company characteristics. Beckers *et al.* (2004) find that there is a positive relationship between the dispersion in analyst forecasts and both consensus forecast error and forecast optimism. Bias and optimism are also an increasing function of past stock return volatility.

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[68] Bartov *et al.* (2002) show that firms that beat revised earnings forecasts enjoy a higher return, despite the expense of dampening expectations prior to the earnings announcement. Perhaps the reported earnings figure is more observable by a greater number of investors.

Mest and Plummer (2003) show that sales forecasts are less optimistically biased than earnings forecasts. The authors argue that the former are less important to the managers of the covered firm; therefore, an analyst has less incentive to intentionally bias such a forecast in order to improve/maintain access to management. The results of Chandra and Ro (2008) appear to confirm this assertion, as they document the increasing importance of revenue (as opposed to earnings) growth in explaining changes in firm valuation.

McNichols and O'Brien (1997) argue that the predominance of positive recommendations is due to analysts' self-selection bias as they tend to predominantly cover stocks for which they have positive views. The authors find that the covered stocks outperform dropped stocks, suggesting that this selection strategy is based on real information rather than conflicts of interest.

It is worth noting that evidence of excessively optimistic forecasts is not necessarily suggestive of analysts' conflicts of interest. Cognitive biases may affect analysts in the same manner that they affect other investors leading to over-optimistic forecasts. Thus, analysts may act like Voltaire's *Dr Pangloss* or Porter's *Pollyanna* of their own accord, rather than at the behest of the management of covered firms. Easterwood and Nutt (1999) assert that cognitive biases lead analysts to overreact (underreact) to good (bad) earnings information, thereby biasing forecasts upwards.

However, there is considerable evidence that the cross-sectional variation in optimism bias is dependent on the gains that an analyst can derive from doing so in terms of underwriting fees and access to information. For example, Michaely and Womack (1999) find that optimism bias is caused by conflicts of interest rather than other explanations, such as cognitive or selection bias. The authors find that optimism is more pronounced for brokerage houses that have a banking relationship with the recommended firm. Similarly, Rajan and Servaes (1997) show that analysts' optimism is more significant for recent IPO firms than a matched sample of firms in the same industry, while Hong and Kubik (2003) show that optimistic analysts are more likely to be rewarded (in terms of career prospects) by their brokerage houses.

Kwag and Stephens (2007) find that Asian-Pacific analysts tend to underreact to negative news, while reacting rationally to positive news, thus issuing systematically optimistic forecasts. Furthermore, analysts tend to underreact (overreact) to recent (old) earnings information. Bhaskar and Morris (1984) and O'Hanlon and Whiddett (1991) find that UK analysts are prone to underreaction when predicting earnings forecasts. Jackson and Johnson (2006) show that analysts underreact to stock returns and corporate actions. This body of evidence may explain short-term momentum and long-term reversal in returns.

Kwag and Shrieves (2010) find that investors are aware of broker bias and incorporate previous forecasts errors when interpreting new earnings announcements[69]. Furthermore, the market reacts to a greater degree to forecast errors when forecasts are historically more optimistic. The authors show that extreme optimistic (pessimistic) errors tend to persist and result in negative (positive) post-announcement drifts over the 60 days following an announcement.

If all forecasts are optimistically biased to a similar degree then such forecasts may be informative if investors discount them in recognition of the optimism bias or analyse forecasts in a relative sense. Wallmeier (2005) finds that the consensus forecasts of German analysts during the market boom of the 1990s were excessively optimistic. However, once the optimism bias is removed such forecasts can be used to generate significant abnormal returns. Ertimur *et al*. (2007) similarly show that significant returns can be generated by interpreting the hold recommendations of conflicted analysts as 'sells' and find that buy recommendations are only profitable for 'non-conflicted' analysts. Similarly, Barber *et al*. (2006) show that upgrades to buy of brokers with a smaller percentage of buys outperform those of brokers with a greater percentage of such optimistic recommendations.

If investors downgrade analysts' recommendations by one degree to correct for bias then it follows that investors would never interpret information as 'strong buy'. This suggests that stock prices will not be informationally efficient as investors' scepticism would prevent them

[69] Agrawal and Chen (2008) and Forbes and Skerratt (1992) also show that investors downgrade brokers' recommendations in recognition of conflicts of interest.

from acting on the occasions where brokers have genuine (unbiased) positive information. Brokers would thus assume the role of Aesop's fabled '*boy who cried wolf*'. Morgan and Stocken (2003) confirm this by showing that analysts are unable to convey the full information content of favourable information but can credibly convey the unfavourable information. The evidence suggests that investors rather crudely discount recommendations, as they do so even for analysts whose incentives are aligned with those of investors.

Malmendier and Shanthikumar (2007) find that large traders revise their trading response to analysts' forecasts downwards in recognition of conflict of interest issues. However, small investors take analysts' recommendations at face value, thereby pushing share prices upward beyond their true values (assuming that analysts' recommendations are indeed biased upwards). Upward bias in stock recommendations is found to be more pronounced when the analyst has an affiliation with the underwriter of the stock (Ljungqvist *et al.*, 2007)[70]. Ferreira and Smith (2006) find that investors have not altered the manner in which they respond to changes in analysts' recommendations in the aftermath of the recent regulation.

Further evidence that investors are wary of taking analysts' buy recommendations at face value is provided by McKnight and Todd (2006), who find that European investors attach greater significance to negative earnings forecasts revisions and are sceptical about positive forecast revisions. Investors adopt a 'wait-and-see' approach, causing a delayed reaction and return continuation for stocks with upward revisions. Analysts' upward revisions contain valuable information but investors may lose out by being over-cynical and only reacting in a delayed fashion.

Barber *et al.* (2007) show that the average daily abnormal return to following the buy recommendations of independent research firms exceeds that of following investment bank recommendations by 3.1 basis points (8% on an annualised basis) during a bear market. The opposite is true with regard to hold and sell recommendations. This suggests that analysts' recommendations are subject to severe conflicts of interest leading to over-optimistic recommendations which are of little economic value, particularly in market downturns.

[70] See also, Bradley *et al.* (2003); Chen (2004); and Barber *et al.* (2006).

There is significant information content in negative recommendations as the analyst must have strong information in order to overcome their reluctance to issue negative advice on an affiliated company.

Moshirian *et al.* (2009) show that the recommendations and revisions of analysts in emerging markets are more positively biased (and are upgraded more often) than those of analysts in developed markets. Furthermore, there is a strong positive relationship between the market-to-book ratio and the issuance of positive recommendations. It appears that analysts favour high growth (glamour) stocks, possibly due to conflicts of interest. Moshirian *et al.* (2009) find that stock prices react strongly, albeit with a lag, to the output of analysts and abnormal returns are possible due to the greater informational asymmetries present in emerging markets.

Abarbanell and Lehavy (2003) attempt to reconcile the apparently contradictory co-existence of vast evidence of analyst optimism, pessimism, and unbiasedness. Abarbanell and Lehavy (2003) find that analysts' forecast errors have a median value of zero and there is a greater prevalence of positive earnings surprises, suggesting pessimism. The authors argue that prior evidence of analyst optimism can be attributed to the greater incidence and magnitude of *extreme* negative earnings surprises ('tail asymmetry'), combined with the contrary finding for small earnings surprises ('middle asymmetry'). Furthermore, 12% of earnings forecasts exhibit zero forecast error.

Cowen *et al.* (2006) show that the level of analyst optimism is dependent on the methods used to fund research. The authors find that optimism is driven more by incentives to generate trading fees than the quest for underwriting fees. Somewhat surprisingly, the authors find that firms that fund their research through underwriting fees issue *less* optimistically biased forecasts.

Additionally, Cowen *et al.* (2006) show that optimism is more significant for analysts employed by retail brokerage firms than their counterparts who issue advice solely to institutional investors. The most optimistic forecasts are issued by brokerage firms who rely on trading revenues but do not generate underwriting fees.

4.5.4 Regulatory efforts

At the turn of the millennium it was widely accepted that the practice of brokers altering their output in the face of conflicts of interest was pervasive. Regulators in the US enacted six key interrelated regulations in an attempt to mitigate conflicts of interest and earnings management, improve the veracity of brokers' recommendations, and reduce information asymmetries by improving the information flow from firms to investors[71]. Efforts to mitigate conflicts of interest in Europe have been less austere and have tended to emphasise guidance towards codes of ethics and self-regulation more than the issuance of concrete rules as is the case in the US (Forbes, 2011).

Several authors report increased informational efficiency in share prices and reduced optimism bias after the regulations were introduced (see, for example, de Jong, 2011; Ertimur *et al.*, 2007; and Barber *et al.,* 2006). However, critics of the regulations assert that they will result in higher information costs and concomitant asymmetries, as analysts will commit fewer resources to following companies. This is confirmed empirically by Irani and Karamanou (2003), Agrawal and Chadha (2002), and Mokoaleli-Mokoteli *et al.* (2009).

Furthermore, Graham *et al.* (2005) posit that the Sarbanes–Oxley Act (2002) has resulted in companies switching their focus from accounting-based to real-based earnings management techniques. The act may thus have a negative impact on shareholder value as accounting measures may be seen to simply alter the timing of earnings; whereas real measures may result in reduced earnings[72].

[71] The six regulations are Regulation Fair Disclosure (2000); NASD Rule 2711 (2002); NYSE Rule 472 (2002); Sarbanes-Oxley Act (2002); Global Research Analysts Settlement (2003); and Regulation Analyst Certification (2003).
[72] This is empirically supported by Cohen *et al.* (2008).

On balance, it appears that the combination of regulations has reduced conflicts of interest and informational asymmetries to a degree; however, analysts' recommendations remain overoptimistic and fail to fully incorporate their private information. It is noteworthy that, the majority of these regulations are limited to analysts operating in the US. It is thus of great interest to compare the output of Irish brokers to those working for American brokerage firms. The results of such an analysis are presented in chapter seven.

4.6 Herding

Since investment decisions involve the processing of large amounts of information investors and brokers may choose to follow the actions of others. Such herding may cause momentum (followed by reversal), as when investors herd they ignore their own private information and prices may thus move away from their fundamental values. Investors may trade excessively as they misinterpret the low dispersion in analysts' forecasts caused herding as indicative of reduced risk. The impact of brokers' herding may be accentuated by investors' commensurate tendency to herd and the phenomenon of 'thought contagion' (Lynch, 2000) as outlined in chapter two.

Welch (2000) finds that analysts are influenced by the prevailing consensus of other analysts as well as the two most recent forecast revisions. This herding behaviour, which Welch (2000) finds to be more prevalent when such a consensus is optimistic and past returns are relatively high, can cause momentum in stock returns. If such herding is irrational (i.e. it is based on mimicry rather than analysts independently following the same fundamental information and arriving at the same forecast), it should be followed by reversal. If analysts are mimicking other analysts then, essentially, they behave like noise traders. Volume levels are higher than those merited by news and the lack of disagreement leads to momentum.

Gleason and Lee (2003) find that investors fail to sufficiently distinguish revisions that contain new information from those that simply move an analyst towards the consensus. Therefore, momentum in returns may be driven by investors reacting to the latter type of revision despite its lack of new information.

Olsen (1996) suggests that the positive bias and poor accuracy of analysts' forecasts stems from herding caused by the human desire for consensus. Keynes (1936, pp.157) outlined the perils of standing out from the crowd when stating that the behaviour of a long-term contrarian trader will be seen as "eccentric, unconventional and rash in the eyes of average opinion". Olsen (1996) shows that herding leads to an increase in the mean because analysts tend to herd their optimistic forecasts more often, as high forecasts lead to greater investment business, and a reduction in the dispersion of analyst forecasts. Investors can misinterpret these two effects as reduced risk and increased future returns. Du and McEnroe (2011) confirm this using experimental data showing that investors are more confident when they receive multiple earnings forecasts with no variability.

De Bondt and Forbes (1999) present evidence of herding among UK analysts. Even as the forecast horizon lengthens (and thus the accuracy of forecast diminishes) herding remains prevalent. Dische (2002) and Liang (2003) find that earnings momentum is more prevalent in stocks with high levels of analyst agreement (low dispersion). In contrast, Verardo (2009) shows that momentum returns in the US are significantly larger for firms with a large dispersion in analysts' forecasts. Bernhardt *et al*. (2006) contradict the above evidence by finding that analysts tend to issue biased contrarian forecasts ('anti-herding'), i.e. forecasts that overshoot the consensus forecast in the direction of their private information.

4.7 Momentum trading by institutions/analysts

Positive feedback trading is not limited to noise traders. There is substantial evidence that professional or institutional traders are trend chasers rather than news watchers. The behaviour of institutional investors is crucial, as in many countries the majority of shares are held by institutions. If such institutions also herd then their effect on the price-setting mechanism will be significant and momentum returns may be largely attributable to institutions engaging in positive feedback trading. Correspondingly, if brokers tend to recommend the purchase of stocks with existing momentum and investors follow this advice, such investors are (perhaps unwittingly) acting as positive feedback traders.

Bange and Miller (2004) find that the behaviour of investment houses is consistent with momentum trading, as recommendations for equity allocation tend to increase for stocks and countries that have performed well over the previous period. Similarly, Doyle *et al.* (2006) show that analyst coverage increases for firms that experienced positive earnings surprises. If investors follow this advice believing it to be based on economic variables then stocks will exhibit momentum that cannot be explained by risk or macroeconomic variables. Doyle *et al.* (2006) confirm this hypothesis by showing that the share prices of such firms tend to drift and a momentum trading strategy that buys (sells) firms with positive (negative) earnings surprises generates significant abnormal returns.

Badrinath and Wahal (2002) show that institutions act as momentum traders when they enter stocks (take new positions) and as contrarian traders when they exit (close) or make adjustments to existing positions. Nofsinger and Sias (1999), Wermers (1999), and Grinblatt *et al*. (1995) also find that institutional investors engage in positive feedback trading. Sorescu and Subrahmanyam (2006) report that approximately half of the abnormal returns to the recommendations of experienced analysts can be explained by momentum, suggesting that such analysts chase trends to some degree. Desai *et al.* (2000) also show that analysts follow momentum strategies.

The task of predicting stock returns that confronts a broker is analogous to a Keynesian 'beauty contest'. Access to relevant information is no guarantee of success in forecasting share prices and issuing recommendations. Instead, analysts must be cognisant of how the majority of investors view the company's prospects. There is little point in an analyst stubbornly swimming against the crowd even if they believe that they have superior information[73]. In fact, Keynes (1936) suggests that predicting the winner of a beauty contest requires one to predict what the average person expects the average opinion to be, rather than predicting what the average opinion will actually be. Analysts are in a unique position in that their output frames the expectations of the public and are often used as a proxy for expectations.

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[73] As J.K. Galbraith says, "In any great organization it is far, far safer to be wrong with the majority than to be right alone."

If the majority of traders follow positive feedback strategies then it may be beneficial for analysts to jump on the bandwagon, even if their information suggests that prices are overvalued. Assuming that the analyst has the informational advantage, share prices will be pushed further away from their fundamental values. This also explains analysts' tendency to herd, as argued by Caparrelli *et al.* (2004) – brokers do not necessarily recommend stocks that they find beautiful but pick stocks that they think will please the majority. Further evidence that analysts' penchant for stocks with existing momentum is provided by Desai and Jain (1995), Womack (1996), Jegadeesh *et al.* (2004), and Jegadeesh and Kim (2006). Azzi and Bird (2005) show that analysts tend to recommend high-momentum *growth* stocks in bull market conditions and high-momentum *value* stocks in bear markets.

Bradshaw (2004) shows that analysts rely heavily on long-term growth forecasts in forming recommendations, even when such growth is impounded into share prices. If such recommendations are taken at face value, share prices may display momentum followed by reversal. Bradshaw (2004) partially supports this thesis by showing that recommendations based on long-term growth are negatively correlated with future returns.

The above dynamics do not apply to the forecasting of earnings per share as these are reported on a specific date and should not contain any noise as they are more objective in nature. Thus, one may expect to see inconsistencies in the forecasting of share prices and earnings per share as the connection between the two variables can break down due to the noise component in share prices.

4.8 Cognitive biases

Naturally, analysts are not emotionless machines that process vast amounts of information in an efficient and unbiased manner. The literature shows that analysts underreact to information in the same way as other market participants. Conservatism, biased self-attribution, overconfidence and other cognitive biases mean that analysts are slow to update their beliefs. Failure to react fully to the information content of news leads to momentum in stock returns.

The substantial evidence suggesting that investors underreact to news was outlined in chapter two. A more substantial market underreaction can be posited if analysts also underestimate the serial correlation in earnings as their forecasts have a more direct and uniform impact on share prices than the actions of disparate investors acting on their own beliefs. Mendenhall (1991) shows that analysts tend to underestimate the persistence of earnings forecast errors. Investors fail to account for this when processing analysts' earnings revisions, thereby explaining the well-documented PEAD and momentum. Similarly, Shane and Brous (2001) confirm the conjecture of Abarbanell and Bernard (1992) that PEAD is driven by the forecasting behaviour of analysts. The authors show that drift in stock returns is attributable to the market correcting for the underreaction of analysts and investors to earnings announcements and analysts' forecast revisions.

However, Abarbanell and Lehavy (2003) show that the asymmetries outlined in section 4.5.3 are responsible for driving the serial correlation in analyst forecast errors. Mean forecast errors following good and bad news are negative suggesting overreaction to good, and underreaction to bad, news. However, Abarbanell and Lehavy (2003) find that forecast errors that follow prior good (bad) news are more likely to fall in the middle (tail) asymmetry. In other words, analysts tend to be optimistic (pessimistic) following bad (good) news, cogently suggesting that analysts underreact to both forms of news. Therefore, evidence consistent with both irrational reactions may be attributable to the extreme nature of optimistic forecast errors and the greater incidence of pessimistic errors.

4.8.1 Overconfidence

Chapter two summarised the considerable body of evidence documenting the psychological bias of overconfidence. This sub-section presents evidence that analysts are equally prone to this bias. Analyst overconfidence (combined with biased self-attribution) may result in momentum as it may contribute to a reluctance to revise forecasts in the face of evidence that contradicts analysts' prior beliefs.

Stotz and von Nitzsch (2005) state that people tend to be more overconfident when they have a stronger perception of control. The authors argue that analysts often have close contact with a company and have earnings forecasts to work with, leading to a greater perception of control and confidence in their ability to forecast earnings. Share price forecasts are more problematic since the price and the discount factor are influenced by investors' behaviour, leading to a perception of less control.

Stotz and von Nitzsch (2005) find that approximately 68% (61%) of analysts feel that their earnings (price) forecasts are superior to their colleagues. Analysts are thus overconfident with regard to both earnings and price forecasts and, as predicted, are more overconfident about the earnings forecasts, about which they feel that they have greater control. This feeling of greater control is confirmed when Stotz and von Nitzsch (2005, p.126) examine some of the analysts' opinions on the difference between earnings and forecasts. Some analysts felt that prices sometimes "happen by chance", are influenced by "irrational investors", and are affected by "general market movements" and "luck". Conversely, superior earnings forecasts are based on "detailed knowledge of the company and the sector" and the "experience" and "hard work" of the analyst (biased self-attribution).

De Bondt and Forbes (1999) also find evidence of overconfidence in analysts' forecasts using UK data. Chen and Jiang (2006) find that analysts tend to overweight their private information when they forecast earnings, especially when issuing forecasts that are more favourable than the consensus. This overweighting increases when the benefits from doing so increase (i.e. incentives to generate commissions). Chen and Jiang (2006) conclude that overweighting may be more attributable to analysts' incentives rather than to cognitive bias (overconfidence and biased self-attribution).

4.9 Geographical considerations

The geographic proximity of a broker to the firms that it covers is an important determinant of the veracity of a broker's forecasts and recommendations in addition to the conflicts of interest that they may face. Coval and Moskowitz (1999) posit an inverse relationship between geographic proximity and the cost of information acquisition. Local analysts are better placed to assess local market conditions, visit the firm and talk to its suppliers, employers, competitors, etc. Malloy (2005) suggests that face-to-face meetings may offer a greater opportunity to obtain valuable private information than is afforded by conference calls. Local analysts focussing solely on companies in their own jurisdiction also avoid the problem of varied accounting standards muddying the waters when forecasting earnings.

Malloy (2005) shows that there is a close relationship between the geographic proximity of analysts to the covered companies and the accuracy of their forecasts. Furthermore, the actions of local analysts have a greater impact on prices, especially when analysts are located in small cities and remote areas. Malloy (2005) asserts that such local analysts tend to have an informational advantage and are not as prone to conflicts of interest caused by a thirst for underwriting fees[74]. Malloy's (2005) study focuses purely on the relationship between distance and forecast accuracy as it focuses on analysts within the US. Thus, the effect of exchange rates, differing accounting standards and other inter-country factors are irrelevant. In contrast, this thesis examines brokers covering Irish shares from a diverse range of countries.

Bolliger (2004) analyses the accuracy of analysts' forecasts in 14 European markets and finds that analysts at small and medium-sized brokerage houses produce more accurate forecasts. Bolliger (2004) finds that forecasting accuracy is negatively correlated with the number of countries covered by analysts, suggesting that large brokerage houses spread themselves too thinly, thereby failing to reap the gains of national specialisation and access to local information. This is consistent with the findings of Desai *et al.* (2000), who show that stocks recommended by *Wall Street Journal* all-star analysts who cover a single industry outperform those of analysts covering multiple industries. Similarly, Boni and Womack (2006) show that any informational edge that analysts can garner is derived from their ability to rank stocks within industries.

[74] The majority of underwriting services are provided by a small number of large banks who are located in major financial centres. Thus, in most cases, analysts in small population centres tend to be unaffiliated to any brokerage houses. However, Malloy (2005) finds that even local affiliated analysts tend to issue less biased recommendations.

This suggest that the forecast accuracy of European analysts may deteriorate over time as there is a continuing trend towards industry specialising, which leads to analysts covering stocks from a greater number of countries (Bolliger, 2004). Surprisingly, Bollinger (2004) finds that forecast accuracy does not appear to improve with experience or for analysts working for large brokerage houses and that the labour market does not reward superior forecast performance[75]. Orpurt (2002) finds that home-country analysts covering German-headquartered firms outperform their foreign-based contemporaries in terms of the accuracy of their earnings forecasts. However, Hendricks *et al.* (2010) find only limited evidence that German banks have superior forecasting abilities to their international counterparts.

Conroy *et al.* (1997) find that local brokerage houses in Japan produce more accurate earnings forecasts than Western brokers operating in Japan, even for firms with which they have no investment banking relationship. Japanese brokers' forecasts are optimistic, but less so than their Western counterparts. It would thus seem that the informational advantage of being local outweighs the conflicts of interest that stem from the desire to generate underwriting fees. This informational advantage stems from local knowledge rather than from access to insider information, as there is no difference in the accuracy of forecasts of affiliated and non-affiliated brokers.

Using a sample of 32 countries, Bae *et al.* (2008) also find that local analysts have a significant information advantage over non-resident analysts. This advantage is greater when there is low volatility in earnings, firms disclose less information to the public, and holdings by insiders are high. This informational advantage is driven by distance rather than the close relationship between local brokerage houses and firms. Foreign analysts become more accurate when they move closer to covered firms and local analysts do not lose precision when they move away, possibly because they maintain superior access to information from the erstwhile proximate firms that they cover.

[75] This is in stark contrast to the findings of Mikhail *et al.* (1997), who document the superior accuracy of the earnings forecasts of more experienced analysts.

Bae *et al.* (2008) find that local analysts have a greater information advantage when covering firms who engage in earnings management and when firms are ranked as having low transparency and poor disclosure. This suggests that the ability of a local analyst to directly contact the firm to quantify the impact of certain information and possibly to engage in the earnings-guidance game facilitates the greater accuracy enjoyed by proximate analysts.

Lai and Teo (2008) find that any informational advantage that analysts in emerging markets possess is overwhelmed by their excessive optimism, which is caused by the pressure to generate investment-banking fees. This home bias results in local analysts' upgrades underperforming those of non-resident analysts, while downgrades outperform their foreign colleagues. Investors fail to account for this bias, resulting in biased recommendations having a significant impact on share prices. This underwriting bias may be more salient for local firms in light of the evidence that investors favour local equities[76].

Salva and Sonney (2011) find that European brokerage research organised along country lines conveys more information than that arranged on a sector basis. The authors show that 'country specialists' produce more valuable forecasts regardless of their proximity to the covered firm. However, it is unclear whether geographical location affects the informational advantage of brokers. Jegadeesh and Kim (2006) show that US analysts are superior at identifying mis-priced stocks than their international counterparts.

4.9.1 The Irish market

There is a dearth of research on the investment advice of analysts in Ireland. Ryan (2006) constitutes the first notable effort to fill this research gap by examining the information content of the written circulars of the four leading Irish-based sell-side analysts. The Irish market differs notably from the major markets that are the focus of the majority of existing studies on brokers. The Irish market has significantly fewer sell-side analysts per quoted company and individual analysts tend to cover more sectors than their US or UK counterparts (Ryan, 2006).

[76] See, for example, Grinblatt and Keloharju (2001b).

The oligopolistic nature of the Irish market may result in a greater prevalence of many of the aforementioned causes of momentum. For example, herding is more likely when there are fewer brokers, while a lack of competition may reduce the importance attached to accurate forecasts and divert the attention towards the numerous conflicts of interest discussed in section 4.5. This is accentuated by the strong historical links between the principal Irish brokers and banks.

Ryan (2006) confirms the findings relating to larger markets by showing that the advice of analysts has a significant impact on share prices and also confirms the propensity for analysts to issue optimistic forecasts. Ryan (2006) documents buy-to-sell ratios of 7.17, or 5.91:1 when similar recommendations made by more than one brokerage house are excluded. The Irish market also displays behaviour consistent with the gradual-information hypothesis and disposition effect as postulated by Hong *et al*. (2000) and Shefrin and Statman (1985) respectively, and there is important information contained in recommendation revisions. Ryan (2006) finds scant evidence of price-following behaviour for buy recommendations.

Ryan (2006) concludes that the relatively high frequency of buy recommendations and the significant market reaction to sell recommendations are caused by analysts' reluctance to issue negative advice in the face of conflicts of interest. There is evidence that hold recommendations may be thinly veiled sell recommendations as such neutral advice elicits a negative market response (-0.91% in the recommending month).

There are high costs to issuing sell recommendations; therefore the benefits from doing so must be sufficiently large. Ryan (2006) finds that the sell recommendations of Irish brokers elicit a far greater market response than buy recommendations. The average return to sell recommendations is -6.45% in the month of recommendation; while the equivalent for buy recommendations is 1.68%. The level of response to sell recommendations in the Irish market seems to be greater than that documented in the US (see, for example, Groth *et al.*, 1979; Elton *et al.*, 1986; Stickel, 1995; Womack, 1996). The market responds to a lesser degree and with less lag to buy recommendations, perhaps because investors discount such recommendations in recognition of conflicts of interest.

Ryan (2006) finds that returns in each of the six months prior to sell and hold recommendations initiations are negative, suggesting that analysts are reluctant to downgrade stocks or that analysts are price traders rather than information traders. The largest negative returns to sell recommendations are recorded in the month prior to the public issuing of the advice; potentially suggesting a leakage of information prior to publication or momentum trading.

Returns to sell recommendations are also negative in the three months following the recommendation suggesting a post recommendations announcement drift caused by delayed reaction. This drift is only present for sell and hold recommendations, consistent with the evidence outlined earlier that investors underreact to bad news (possibly due to the loss aversion driven disposition effect). Ryan (2006) posits that it may take investors some time to realise that hold recommendations are in fact disguised advice to sell. This explains the finding that hold recommendations result in negative returns for ten consecutive months, the largest of which is recorded two months after the recommendation is issued.

4.10 Summary and conclusions

There are two major pillars that must exist in order to support the theory that brokers are to some extent responsible for the stylised anomalies of momentum and reversal in share prices. First, conflicts of interest, cognitive biases, herding, momentum trading or some other underlying motivation must cause brokers to issue forecasts and recommendations that are excessively optimistic and are consistent with the continuation of past performance. Second, investors must interpret such recommendations at face value, failing to account for cognitive biases and conflicts of interest, and trade in such a way that causes continuation, pushing share prices beyond their fundamental values. Momentum is more probable if such investors overreact to the advice of brokers and react in a delayed fashion.

This chapter has outlined the rich body of evidence that strongly suggests that these two pillars are firmly embedded in financial markets, despite extensive regulatory efforts, principally in the US. Brokers are prone to conflicts of interest causing them to issue overly optimistic forecasts and recommendations. They also herd and recommend stocks that have existing momentum. Investors tend to take brokers' advice at face value and such recommendations and forecasts thus impact share prices. This often occurs in a delayed fashion, as the output is disseminated to investors at different intervals and investors often trade on old information and have a tendency to herd and overreact to information. Brokers' advice is often of insignificant economic value but investors trade on it nonetheless, thereby pushing share prices beyond their fundamental values, leading to a subsequent reversal. Taken together, the evidence presented in this chapter paints a vivid picture of brokers playing a central role in the dynamics of the momentum and reversal anomalies.

The anomalies may also be driven by companies and brokers engaging in an earning-guidance game that not only deteriorates the quality of reported accounting information but also compromises the real activities of companies resulting in an inefficient use of scarce resources and thus an economic loss to society. Recent regulatory efforts to tackle this problem may have merely altered the channel through which companies manage earnings. This may have resulted in a greater pervasiveness of myopic value-destroying efforts to manipulate the real activities of a company. Future efforts to improve the output of brokers and the behaviour of companies may be better served by addressing the incentive structures that drive the behaviour of both parties rather than attempting to close the avenues of such behaviour.

The chapter shows that research is almost exclusively restricted to large developed markets such as the US and the UK, with a conspicuous dearth of research on small markets. There is also a paucity of research pertaining to the impact of competition levels in the market for brokerage advice. Chapter seven attempts to fill this void by analysing the oligopolistic brokerage market in Ireland.

Chapter Five

Data and Methodology

5.1 Introduction

This chapter outlines the data and methodology employed in testing the existence of momentum and reversal in returns and the accuracy and impact of brokers' recommendations and forecasts. Section 5.2 presents details of the datasets that are constructed for these tests. Sections 5.3 and 5.4 discuss the methodological approaches relating to the anomalies and brokers respectively, while the limitations of the data and methodology are outlined in section 5.5.

5.2 Data

This section presents details of the data used for the two principal strands of the thesis. Section 5.2.1 outlines the dataset employed to estimate the returns to the contrarian and momentum strategies; section 5.2.2 discusses the data pertaining to the output of brokers.

5.2.1 Return reversal and continuation

This study employs data from four medium-sized European markets; Ireland, Greece, Norway, and Denmark in order to examine the reversal and momentum anomalies. Share-price and market-index data is obtained from Thomson One Banker's Datastream online data service. One Banker is a widely used and accepted database. The period of study is 1989-2006, with the period 2007-09 being used to test the out-of-sample validity of the results. Stock prices are taken as the closing price on the Friday of each week[77]. The year 1989 was chosen so as to avoid the effects of the stock-market crash in October 1987. Datastream uses mid-market prices, thereby reducing bid-ask spread bias.

[77] The use of monthly share prices did not alter the results significantly.

The study examines the top stocks by market capitalisation at the beginning of each portfolio formation period as well as an asset that is an average of a selection of smaller stocks listed at that date. Stocks that delist during a holding period are sold and the proceeds are divided equally among the remaining stocks. Including stocks that delist avoids problems of survivorship bias and is more representative of the *ex-ante* decisions faced by an investor.

Furthermore, there was an approximately equal spilt between firms delisting due to mergers and acquisitions and those due to financial distress. On average, the abnormal returns of delisted firms were not statistically different to surviving firms in the year prior to delising. Therefore, one can conclude that there is no *systematic* bias introduced.

By examining the top assets quoted on each stock exchange, as ranked by market capitalisation, this study will make it easier to distinguish between the winner-loser and momentum effects and the size effect and reduce problems of 'thin trading', as it will only be relatively large companies that are used. Furthermore, Siganos (2010) recommends that investors should focus on a small number of large companies in order to minimise transaction costs.

The number of stocks used to form the winner and loser portfolios is small relative to much of the existing research in this area. The number of shares in each portfolio ranges from six to 15 with an average of 11 shares being held[78]. Thus, the transaction costs will be relatively low since most investors pay a flat fee for each trade. Furthermore, holding periods are non-overlapping meaning that round-trip transaction costs are only incurred once every three years for the contrarian strategy and once a year for the momentum strategy (excluding re-balancing for delisted stocks). Although the use of non-overlapping periods results in fewer holding periods, it maintains return independence, as stated by Schiereck *et al.* (1999). This ensures that there is no need to adjust standard errors for serial dependence.

It is felt that these results will be of more relevance to small investors as well as fund managers, as Goetzmann and Kumar (2008 cited in Siganos, 2010) find that the average

[78] Siganos (2010) finds that it is optimum for an investor to hold 20 winners and 20 losers.

shareholding of a US investor is $35,629, with most investors only holding three or four stocks. Thus, a momentum strategy that buys and sells small quantities of a diverse range of stocks would not be exploitable for the majority of small investors.

The ISEQ index, KFX, Athens Comp, and OSEBX, which are value-weighted indices, will be used as a market index in order to estimate abnormal returns. The four stock exchanges are similar in terms of market capitalisation as of May 2010. Norway is the largest with a market capitalisation of €136bn, followed by Greece (€63bn). Denmark is the third largest (€48bn), narrowly larger than Ireland (€44bn). These relatively small differences in size allow for a sensible comparison but also facilitate an investigation into any correlation between the size of the market and the extent of any anomalous returns discovered.

The sample in two of the markets is highly concentrated in a small number of industries. In Norway, oil and shipping firms account for in excess of 50% of market capitalisation, while pharmaceuticals and biotechnology firms account for almost 50% of market capitalisation in Denmark. There is no dominant industry in Ireland or Greece.

Table 5.1 presents summary statistics on the companies analysed in each market. Panel A lists the total number of companies in the dataset. Naturally, not all companies are listed for the entire sample period. Thus, Panel B presents summary statistics on the number of stocks analysed for the contrarian investment strategy[79]. Panel C presents summary statistics on firm-specific attributes of the average and median firm. Such statistics are computed over the entire sample period (1989-2009) and those from Norway and Denmark are converted to euros using exchange rates from the end of each calendar year.

[79] The statistics for the strength rule portfolios are virtually identical.

Table 5.1

Number of companies analysed

Panel A shows the total number of companies analysed in each country. The main list refers to the large companies that are bought or sold as individual stocks, while the remaining companies are grouped into a portfolio of small firms in order to overcome problems associated with thin trading. The figures represent an upper limit on the number of companies used in each holding period as not all companies are listed for the entire sample period. Thus, Panel B reports summary statistics on the number of companies used in each holding period. The small company index is counted as one stock and the figures reported are for the contrarian investment strategy. Panel C reports the mean (median) value of a number of firm-specific variables.

Panel A: Number of firms

	Ireland	Greece	Norway	Denmark
Main list	32	34	36	27
Small company portfolio	24	28	11	14

Panel B: Number of stocks per holding period

Market	Mean	Median	Minimum	Maximum
Ireland	24.2	25.5	18	26
Greece	19.0	18	12	28
Norway	22.7	23.5	16	28
Denmark	21.7	22	18	26

Panel C: Firm-specific attributes

Variable	Ireland	Greece	Norway	Denmark
Size (€m)	3257 (1354)	626 (289)	4705 (1180)	6785 (2424)
P/E	25.6 (14.4)	12.8 (8.3)	21.4 (14.0)	26.0 (19.3)
B/M	0.1 (0.6)	1.4 (2.0)	0.6 (0.7)	0.3 (0.6)
Share price (€)	15.9 (4.9)	8.6 (8.4)	11.2 (8.5)	174.5 (24.6)[80]
Beta	0.89 (0.82)	0.97 (0.91)	0.89 (0.93)	0.81 (0.88)

[80] The high average share price in Denmark is largely attributable to AP Moller; the average price of the remaining firms is €29.10.

5.2.2 Brokers' recommendations and forecasts

The output of brokers is analysed using panel data relating to publicly-traded Irish firms. The panel is comprised of time-series data along the cross-sectional dimensions of brokers' output and firm-specific characteristics. Brokers' opinions on covered firms are measured with reference to price forecasts, recommendation levels, and EPS forecasts. Revisions to the former two measures are also analysed. Firm-specific variables include past momentum and volume and accounting ratios, such as book-to-market and earnings-price.

All data is sourced from the Thomson ONE Banker database for the time period July 1999 to July 2009. This period incorporates various economic states, which increases the robustness of the findings. In times of extreme unexpected economic growth (decline) previous forecasts will appear to be extremely pessimistic (optimistic) *ex post*, but at the time of forecasting this may not have been the case. Weekly data is used for all variables, yielding a maximum of 520 observations per company for each broker.

The sample is limited to firms that are followed by at least three brokers and have matching accounting data. The resulting dataset includes the output of 77 brokers, covering 26 companies listed on the Irish stock exchange. A total of 45,918 price forecasts, 16,560 EPS forecasts, and 70,794 recommendations are analysed. In addition, 2,262 target price and 1,094 recommendation revisions are examined.

To the author's knowledge this is the largest dataset used in a study of the Irish brokerage industry. Ryan (2006) obtains a total of 398 recommendations from the written circulars of four brokerage houses for an 18-month period. The sample size also compares favourably to those of studies examining larger markets where the number of publicly traded companies is significantly larger than is the case for Ireland.[81]

The Irish brokerage industry is oligopolistic in nature and is dominated by Goodbody and Davy stockbrokers. The remainder of the market is largely divided between NCB and Merrion stockbrokers. Such a concentrated industry is of great interest, as oligopolistic

[81] See appendix C for details of the sample sizes of some key studies.

practices and implicit collusion may lead to a greater level of herding than in more competitive markets. The problem of overconfidence and positive bias may also be more prevalent in the Irish market as all major players in the market have traditional links to banks, potentially making conflicts of interest more prevalent. Furthermore, Irish brokers are not subject to same regulatory framework as their American counterparts. This thesis investigates whether this results in conflict of interest driven bias remaining high for Irish brokers.

The summary statistics relating to the brokerage data are presented in table 5.2 along the dimensions of brokerage firms and covered companies. Coverage is dominated by the output of a small number of Irish brokers, covering a relatively small number of firms. The top decile of brokers account for 45, 54, and 50% of the total number of price forecasts, earnings forecasts, and recommendations respectively. The two lowest deciles account for 1% of output. This level of concentration is greater than that reported in other markets[82]. Detailed breakdowns of the following statistics by firm and broker are contained in appendix D and E respectively.

Coverage in also dominated by a small number of the 26 covered companies. The two (five) most covered companies account for approximately one-quarter (half) of all brokers' output. The five-firm concentration ratios for price forecasts, earnings forecasts, and recommendations are 51, 40, and 53% respectively. The most covered company is followed by almost two-thirds of the brokers, while the mean (median) coverage is approximately 20% (14%).

[82] For example, the top ten brokers account for almost 74% of all output, compared to approximately two-thirds in the UK as reported in De Bondt and Forbes (1999).

Table 5.2

Analyst following

The table presents summary statistics on broker coverage. Panel A outlines coverage in terms of the number of brokers that follow each firm, while Panel B details the number of firms that each brokerage firm follows.

Panel A: Number of brokers covering firms

	Target price	Recommendation	EPS
Mean	12.15	14.96	9.00
Median	8.50	11.00	6.50
Minimum	3	2	3
Maximum	34	46	25

Panel B: Number of firms covered by broker

All	Target price	Recommendation	EPS
Mean	4.09	4.92	3.03
Median	2.00	3.00	1.00
Maximum	26	26	25
Irish			
Mean	22.5	18.5	23.5
Median	22.5	24	23.5
Non-Irish			
Mean	3.1	4.2	1.9
Median	1	3	1

Four of the 77 brokerage firms in the sample are Irish and they account for 35% (47%) of price (EPS) forecasts, while the three[83] Irish brokers issued 30% of the recommendations. Irish brokers occupy the top three positions in all categories. There is a marked difference between the coverage of Irish and non-Irish brokers. The former cover virtually all of the

[83] The database did not contain recommendation categories for Davy Stockbrokers.

companies in the sample, while the latter focus on a relatively small number of firms[84]. Table 5.3 presents summary statistics on the output of brokers.[85]

Table 5.3

Summary statistics for brokers' output

	Price forecasts	EPS forecast	Recommendations
Mean	792	359	306
Median	260	94	931
Maximum	6,085	2,843	8,090
Total	45,918	16,153	70,794

Consistent with the underwriting hypothesis, bivariate analysis shows that there is a strong relationship ($r = 0.90$) between the number of recommendations issued for a company and the value of that company's traded stock.

5.3 Contrarian and strength rule methodology

This section discusses the methodology employed in the two overarching strands of the research. This study employs Cumulative Abnormal Returns (CARs) to calculate the returns to the two trading strategies under investigation. CARs employ natural logarithms of prices in order to obtain continuously compounded (as opposed to simple) returns. The continuously compounded return, R_{it}, is calculated as the natural logarithm of the ratio of the share price for the current and previous time period (p_t and p_{t-1} respectively):

$$R_{it} = ln\left(\frac{P_t}{P_{t-1}}\right) \qquad (5.1)$$

[84] This does not necessarily imply that Irish brokers are less specialised in terms of the industries that they follow. One would expect that there are more analysts in the Irish brokerage houses focusing on Irish firms. Hence, one would expect that a greater number of firms will be followed. In the absence of data on individual brokers one cannot comment on industry specialisation.
[85] The average number of forecasts/recommendations is limited by the fact that a number of companies under review were not listed for the entire sample period.

An analogous equation is used for calculating market returns using index data. Log returns are favoured in many event studies due to their time-additive[86] nature and because they are shown to more closely resemble a normal distribution than simple returns. Corrado and Truong (2008) show that returns calculated using logarithms produce superior test specifications than those calculated using arithmetic returns. For all models abnormal returns are measured with reference to market returns. Details of the index used from each of the four markets are presented below.

Table 5.4

Market indices

The table presents details of the market indices employed for the purpose of calculating market returns. All index data is sourced from Thomson One Banker.

	Ireland	**Greece**	**Denmark**	**Norway**
Index	ISEQ overall	ASE	KFX	OBX
Number of stocks	All stocks	60 largest companies	20 most traded stocks	All stocks
Weighting	Value	Value	Value	Value

5.3.1 Return-generating models

This study uses three models in order to measure abnormal returns; the market model; the Capital Asset Pricing Model **(**CAPM); and the market adjusted model, as with De Bondt and Thaler (1985). The CAPM is an equilibrium model developed by Sharpe (1964) and Lintner (1965). It models expected return in terms of undiversifiable (systematic) risk. The standard *ex-ante* and *ex-post* equations for the CAPM are respectively:

$$E(R_i) = R^* + \beta_i \, [\, E(R_m) - R^*] \qquad (5.2)$$

$$R_{it} = R_t^* + \beta_i \, (R_{mt} - R_t^*) + \varepsilon_{it} \qquad (5.3)$$

[86] Consider the case where a stock price increases from €1 to €1.25 and then falls back to €1. The sum of the simple returns will be 5% (the sum of +25% and -20%) even though the overall return is zero. Calculating cumulative returns $(1+r_1)(1+r_2)$ -1 gives the correct return of zero ([1.25*0.8] – 1). Similarly, the sum of the log returns (0.2231 – 0.2231) will also be zero.

Where:

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

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

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

β_i is a measure of systematic risk = $Cov(R_i,R_m)/Var(R_m)$ and

ε_{it} is a random error.

The three-month inter-bank rate is used for the risk-free rate of return[87]. In using the CAPM one must keep in mind, *inter alia*, Roll's critique, where in practice using broad-based market indices such as the ISEQ index may not be theoretically sound (Cuthbertson, 1996, pp.73-74).

Two variants of the market model are also used in order to estimate abnormal returns; the market model and the market-adjusted model. The market model developed by Sharpe (1963) was the first attempt to simplify portfolio theory by arguing that shares move to varying degrees in line with the market itself. Unlike the CAPM, the market model looks not only at the pricing of undiversifiable market risk but at total risk i.e. market risk plus specific company risk (Pilbeam, 1998, pp.146-148). Sharpe (1963) postulates a linear relationship between the return on a security and that of the market as a whole. The *ex-post* equation is given by:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \qquad (5.4)$$

Where α_i is a constant factor that varies between securities and measures the return to a stock when there is no movement in the market. The market-adjusted model imposes a restriction in (5.4) that α_i is zero and that β_i is equal to one.

$$R_{it} - R_{mt} = \varepsilon_{it} \qquad (5.5)$$

[87] In order to calculate the geometric weekly interest rate, r_W, from the annual rate, r_A, the formula $r_W = \{[1+r_A]^{1/52}-1\}*100$ was used.

This study uses equations (5.2)-(5.4) in modelling equity returns. In each case the error term (ε_{it}) is interpreted as the abnormal return. The profitability of this contrarian investment strategy is calculated as the difference between the cumulative average excess returns of the loser portfolio and that of the winner portfolio, as the strategy involves buying the former and short-selling the latter. The opposite is the case for the strength rule. The market model uses a single beta for the whole dataset, whereas a separate beta is calculated for each rank and holding period for the CAPM. The CAPM thus deals with risk more thoroughly than the two market models.

The Fama-French three-factor model is not used as the factors are not available for the four markets under review. Fama and French (2011) include all four markets in their European portfolios. However, there is still an absence of loading factors and portfolio returns for each of the four markets analysed in this study at the individual-country level. It is reasonable to expect that the average factors are dominated by stocks from larger markets, such as Germany, UK, and France. Furthermore, Griffin (2002) shows that country-specific factors are superior to global factors.

5.3.2 Portfolios

For the contrarian strategy, three-year samples of share prices are taken, as with De Bondt and Thaler's (1985) study. The first three-year period in which winners and losers are identified is known as the *rank period.* The following three-year period in which the performance of these stocks is analysed is known as the *test (holding) period.* Two equally-weighted portfolios are set up, one comprising former winners and the other comprising former losers and the cumulative abnormal returns (CAR) for each portfolio for each non-overlapping test period will be calculated to test the profitability of a contrarian investment strategy.

For the contrarian strategy, the period 1989-1991 is formation period number one, 1992-1994 is formation period number two and test period number one. This process is repeated until the final holding period (2004-06). For the strength rule, each year from 1989 to 2005 is a portfolio formation periods and each year between 1990 and 2006 is a test period. The period 2007-09 is used to test the out-of-sample forecasting power of the results. This period allows for one (three) holding period(s) for the contrarian (strength rule) strategy.

Small firms are grouped together into a separate portfolio that represents one asset. The returns on this portfolio are evaluated in the same manner as other (individual) stocks. This portfolio is used in order to minimise the risk that the results are skewed by the returns of small thinly traded (and illiquid) securities, which would be expected to have higher bid-ask spreads. Companies are classified as 'small' if their market capitalisation accounts for less than 0.1% of the overall market capitalisation. The total number of companies analysed is 206. Of these, 77 qualify for the small company portfolio.

The relatively small number of stocks on the four markets under review negates the use of deciles, as employed in studies on larger markets. In examining momentum on the Irish market, O'Sullivan and O'Sullivan (2010) utilise portfolios based on the top and bottom 30%, 10%, and five stocks, while O' Donnell and Baur (2009) construct portfolios based on the top and bottom third of stocks. Similarly, Naranjo and Porter (2007), whose sample includes all four markets that form the basis of this study, construct portfolios using the top and bottom three deciles.

This study classifies winners (losers) as the top (bottom) half of stocks[88] and will also form extreme portfolios comprised of the top and bottom two and four stocks. Returns are calculated using equally-weighted portfolios[89]. Cumulative abnormal returns for a portfolio (CAR_{pt}) are calculated by averaging the abnormal returns for *n* stocks for each period *T*, i.e:

$$CAR_{pt} = \frac{1}{N}\sum_{t=1}^{T}\sum_{i=1}^{n}\varepsilon_{it} \qquad (5.6)$$

[88] Where there is an odd number of stocks, the middle stock is omitted.
[89] The use of value-weighted portfolios did not alter the results materially.

The profitability of the contrarian investment strategy is calculated as the difference between the cumulative average abnormal returns of the loser portfolio and that of the winner portfolio (CAR_L-CAR_W), as the strategy involves buying the former and selling short the latter. These excess abnormal returns are averaged for the five three-year holding periods to give the overall average profitability of the strategy. An analogous process is followed for the strength rule strategy; excess abnormal returns (CAR_W-CAR_L) are averaged over the 17 non-overlapping one-year holding periods.

5.3.3 Statistical significance

The statistical significance of abnormal returns to the contrarian and strength rule strategies is estimated using the approach of De Bondt and Thaler (1985). The following equations describe the process employed for obtaining test statistic relating to the contrarian strategy. De Bondt and Thaler (1985) estimate the t-statistic of the excess abnormal return (i.e. loser minus winner returns) as:

$$T_t = \left[ACAR_{L,t} - ACAR_{W,t}\right] / \sqrt{2S_t^2/N} \quad (5.7)$$

Where $ACAR_{W,t}$ and $ACAR_{L,t}$ are the average abnormal returns of the winner and loser portfolios, respectively, and $2S_t^2$ is the pooled estimate of population variance in CAR_t and is estimated as:

$$\left[\sum_{n=1}^{N}\left(CAR_{W,n,t} - ACAR_{W,t}\right)^2 + \sum_{n=1}^{N}\left(CAR_{L,n,t} - ACAR_{L,t}\right)^2\right] / 2(N-1) \quad (5.8)$$

Assuming samples of equal size, N, the sample standard deviation for the winner portfolio is estimated as:

$$S_t = \sqrt{\sum_{n=1}^{N} \frac{\left(AR_{W,n,t} - AR_{W,t}\right)^2}{N} / N - 1} \quad (5.9)$$

The standard error is then calculated as the standard deviation divided by the square root of N and the t-statistic is the abnormal return of the winner portfolio divided by the standard error. The equivalent statistic for the loser portfolio is calculated using the same approach. The test statistics for the strength rule are estimated in a similar manner with equation 5.7 being modified to:

$$T_t = \left[ACAR_{W,t} - ACAR_{L,t}\right] / \sqrt{2S_t^2/N} \quad (5.10)$$

The test statistics will follow Student's t-distribution if abnormal returns are normally distributed. A number of tests of normality were conducted and confirmed that this was the case.

5.3.4 Robustness tests

This study conducts three general tests in order to assess the robustness of any abnormal returns. First, the out-of-sample robustness of the key findings is examined by analysing the pattern of returns in the period 2007-09. Second, an analysis of sub-period returns is conducted, in order to assess whether any positive average abnormal returns are largely attributable to the extremely profitable performance of the strategy in a small number of sub-periods. Finally, a number of methods are employed to ascertain whether any abnormal returns are driven by the dynamics of a relatively small number of stocks. Further details of each of these procedures are outlined in section 6.5.

5.4 Brokers' output methodology

The accuracy and impact of brokers' output are analysed using both calendar and event based strategies. The first part of the analysis represents a calendar-time study, where the output of analysts is examined at the consensus level at the end of each calendar quarter. The remaining analysis constitutes an event study, where the initiation and revisions of broker measures are analysed at the level of individual brokers in event time.

Various test periods are employed, ranging from a minimum of one week to a maximum of six months before, and one year after, the event date. Such an extended event window is employed due to possible leakages and delayed reactions, as discussed in chapter four. Furthermore, recommendations are often republished in the financial press. Thus, it is often difficult to ascertain a precise date that the market becomes aware of an event.

A disadvantage of employing an extended test period is that there is a greater probability of encountering multiple events within the same test period. This can result in cross-sectional dependence problems, which understate standard errors and inflate test statistics. This issue is overcome with a novel approach, which excludes overlapping observations, as will be discussed in section 7.6.

Abnormal returns are measured using the adjusted-market model (equation 5.5) and buy-and-hold returns, in order to facilitate comparisons with existing studies relating to brokers' recommendations. Furthermore, the percentage of recommendations falling into each category is calculated, in order to assess whether analysts are biased (possibly due to conflicts of interest) towards positive recommendations. The subsequent performance of recommendations is examined in order to ascertain whether any biases lead to inaccurate and overoptimistic forecasts.

Brokers use a myriad of terms and a varying number of categories in order to communicate their opinions on the prospects of the firms that they follow. In order to analyse these recommendations it is necessary to convert them into a standard format. The key dimension along which existing studies differ is the number of categories employed. Several studies (for example, Stickel, 1995; Welch, 2000; Jegadeesh *et al.*, 2004; Barber *et al.*, 2007) utilise separate categories for strong buy and strong sell and merge both add and buy and reduce and sell, as they rely on the categories reported by the Zacks Investment Research, First Call, and IBES[90] databases. In contrast, Ryan (2006) uses three discrete categories; buy, hold, and sell.

[90] IBES categorises recommendations as strong buy, buy, hold, underperform, sell and strong sell. However, studies often amalgamate these into broader categories (see, for example, Moshirian *et al.*, 2009).

This study differs from the above two approaches by using buy, add, hold, reduce, and sell for three reasons. First, it is felt that the inclusion of separate categories for 'strong buy' and 'strong sell' is of limited use. In a dataset of 70,794 recommendations, there are only 419 observed 'strong buy' recommendations (less than 0.6% of the overall sample) and no 'strong sells'. Therefore, no distinction is made between strong buys and buys, as the former group would not be sufficiently populated to merit a separate category. This approach is similar to that adopted by Jegadeesh and Kim (2006), who merge 'sell' and 'strong sell' recommendations.

Second, the above approaches merge the 'add' and 'buy' and 'reduce' and 'sell' categories. It is felt that doing so would truncate the data into a restrictively small number of categories and result in the loss of a key distinction between the information content of each category. It is strongly felt that the five categories are necessary in order to distinguish between the 27,309 buy and 16,868 add recommendations and between the 3,597 reduce and 1,958 sell recommendations. A distinction between the 27,309 buy and 419 strong buy recommendations is seen as less illuminating and there are no strong sells to isolate from the sell recommendations.

Third, the five-point rating system most closely represents the scales used by brokers in this sample, with its users accounting for in excess of three-quarters of recommendations. In order to populate each of the five categories a manual coding was conducted by analysing the recommendations of each broker and assigning it into the appropriate category. Table 5.5 details the interpretation of the various terms used by brokers in their final recommendation, ranging from positive (bullish) to negative (bearish). Rakings of 1-5 (sell =1, … buy = 5) are attached to these categories and will be used to calculate an optimism index[91].

[91] The above approach may bias the average recommendation value upwards for brokers who only use sell, hold, buy. However, the results were not materially affected when a value of 4.5 (1.5) was attached to buy (sell) recommendations.

Table 5.5

Rating system used to code recommendations

5	4	3	2	1
Buy	Add	Hold	Reduce	Sell
Strong buy	Accumulate	Neutral	Underperform	
	Buy on weakness	Market perform	Underweight	
	Outperform	Equalweight		
	Overweight	In-line		
		Peer perform		

In order to gain an understanding of the characteristics of the stocks that brokers recommend favourably, quintiles are formed based on recommendation levels and the firm-specific characteristics of the constituents of each quintile is analysed. The future abnormal returns and volume associated with each quintile are also examined in order to assess the price and volume impact of brokers' recommendations. Rank correlation coefficients are also calculated for all pairs of variables. This will provide an insight into whether brokers follow momentum or value strategies and whether their output is influenced by conflicts of interest.

The price and volume effects to quintiles sorted on each of the other firm-specific variables is also estimated in order to evaluate whether brokers add incremental value above what is contained in publicly available information such as momentum, firm size, and book-to-market. The approach largely follows that of Jegadeesh *et al.* (2004) with a number of minor adjustments. Due to a lack of data, several variables, such as sales growth, total assets, and standardised unexpected earnings, are omitted, while measures for dispersion and future volume are added to the suite of variables. Furthermore, analysts' views on the prospects of a firm are measured using the expected price change variable in addition to ratings levels.

This above approach employs calendar-time tests by forming quintiles for each of the 36 quarters in the sample period, which runs from July 2000 to June 2009[92]. Fama and French (2008) state that decile approaches can be unreliable as extreme portfolios often contain

[92] Stocks are added to the quintiles in such a way that the extreme quintiles always contain the same number of stocks as each other. In other words, if there is an odd (even) number of additional stocks they are placed in the middle (extreme) quintile(s). The results are not materially affected by the omission of these observations.

extremely small stocks. Such stocks are overrepresented relative to their share of market value when equal-weight portfolios are employed. By using quintiles and limiting the sample to relatively large firms, this study minimises this potential problem. The following sub-sections provide details of the variables that are analysed. For all variables, time *t* refers to the three months to the end of the calendar quarter.

5.4.1 Analysts' views

Four variables are used in order to capture analysts' views of the prospects of each firm. Consensus recommendation levels and the expected price changes are examined, along with changes in these two measures. The hypothesised relationship between all four measures and future abnormal returns is positive.

Rating refers to the consensus forecast ($\bar{A}_t$) for each firm and is calculated as the mean of the most recent recommendation (A_{it}) for each broker in the three months prior to each calendar quarter end. Recommendations are coded from sell =1 to buy =5 as detailed in table 5.5.

$$\bar{A}_t = \frac{1}{N} A_{it} \qquad (5.11)$$

Ratings changes

Jegadeesh *et al.* (2004) find that recommendations changes provide more valuable information than recommendation levels. The recommendation change (Δ **Rating)** is the change in the mean level between the end of the prior calendar quarter and the current calendar quarter.

$$\Delta\bar{A}_t = \bar{A}_t - \bar{A}_{t-1} \qquad (5.12)$$

Expected price change

Analysts' views on a firm's prospects are also measured using the anticipated percentage price change implied by price forecasts. The continuous nature of this variable provides a superior basis for analysis to the discrete recommendation level as it facilitates a more precise assignment of stocks to the relevant quintiles.

EXP takes the difference between the most recent forecast prior to the end of the calendar quarter and the price at that date and scales by that price.

$$EXP_{it} = \frac{F_{it} - P_{it}}{P_{it}} * 100 \qquad (5.13)$$

Revisions are measured by Δ**EXP**, which is the change in EXP between consecutive quarters. In terms of quintile formation, Δ **EXP** is a superior measure to Δ **Rating**, as price forecasts are revised more often than recommendation levels. On average, there is one revision for every 65 recommendations; the equivalent figure for price forecasts is 20[93]. This reluctance of analysts to revise their recommendations leads to a relatively large proportion of instances where Δ **Rating** is zero. Assigning such observations to quintiles becomes subjective and accordingly, non-extreme quintiles must be interpreted with caution.

5.4.2 Momentum

Several authors, such as Womack (1996) and Jegadeesh and Kim (2006), find that analysts tilt their recommendations towards stocks with high momentum in light of the findings of Jegadeesh and Titman (1993) that future returns are positively correlated with past returns. Momentum is captured using past returns over three- and six-month periods. **MOM(3)** measures momentum before the calendar time *t* and is calculated as the cumulative market-adjusted returns for each firm from week *t-13* to *t-1*.

[93] There are 2,262 (1,094) revisions in 45,918 (70,794) forecasts (recommendations).

$$RET(3)_{it} = \prod_{t=-13}^{t=-1}(1 + R_{it}) - \prod_{t=-13}^{t=-1}(1 + R_{mt}) \qquad (5.14)$$

MOM(6) follows the same approach with returns cumulated between week -1 and -26.

5.4.3 Firm size

Banz (1981) documents a negative relationship between firm-size and returns. **SIZE** measures the natural logarithm of the number of shares outstanding (N_{it}) for each firm multiplied by the corresponding share price at the end of the quarter (P_{it}).

$$\mathrm{SIZE}_{it} = \ln(N_{it} \text{ x } P_{it}) \qquad (5.15)$$

5.4.4 Dispersion

Erturk (2006) reports a negative relationship between dispersion and future abnormal returns. **DISP** is measured by the coefficient of variation, which is calculated by scaling the cross-sectional standard deviation of price forecasts by the mean forecast (see, for example, Dische, 2002).

$$\mathrm{DISP}_{it} = \frac{\sigma_{it}}{\bar{x}_i} \qquad (5.16)$$

5.4.5 Past volume

According to Jegadeesh *et al.* (2004), analysts may be more likely to favourably recommend low-volume stocks in light of the finding of Lee and Swaminathan (2000) that such stocks exhibit value characteristics and earn higher future returns than high-volume (growth) stocks. However, Jegadeesh *et al.* (2004) find that stocks with higher trading volume receive more favourable recommendations and revisions, despite subsequently earning lower abnormal returns. The relationship between volume and ratings may be clouded by any strong relationship between high volume and high momentum[94].

Abnormal volume, **VOL,** is a measure of standardised volume and is calculated as the ratio of average weekly volume for the current quarter volume to the average of the preceding three quarters.

$$VOL_{it} = \frac{V_{it}}{\frac{1}{3}(V_{it-1} + V_{it-2} + V_{it-3})} \qquad (5.17)$$

Where V_{it} is the average weekly volume over 13 weeks before the end of calendar quarter.

5.4.6 Book-to-market

Fama and French (1992) document a positive relationship between book-to-market (B/M) ratios and abnormal returns. If brokers follow value (growth) strategies then one would expect to observe a positive (negative) relationship between B/M and recommendation levels. **B/M** divides the book value at the end of each calendar quarter by the firm's market capitalisation.

$$BM_{it} = \frac{\text{Book value of common equity}_{it}}{\text{Market capitalisation}_{it}} \qquad (5.18)$$

Book value is calculated as the net assets of each firm at the end of the calendar quarter. Market capitalisation is calculated as the number of shares outstanding at the end of the calendar quarter multiplied by the contemporaneous share price. Negative book-to-market ratios are omitted as failing to do so would result in skewed averages.

[94] However, Jegadeesh *et al.* (2004) show that the relationship between volume and ratings is robust to adjustments that account for this correlation.

5.4.7 Earnings-price ratio

Basu (1977) documents the superior performance of firms with high earnings-to-price (E/P) ratios. Jegadeesh *et al*. (2004) find that analysts follow value (contrarian) strategies by favourably recommending such firms. **E/P** takes the earnings per share before extraordinary items for each firm divided by its share price at the end of the quarter. Firm quarters with non-positive EPS are excluded.

$$E/P_{it} = \frac{EPS_{it}}{P_{it}} \qquad (5.19)$$

5.4.8 Future returns and volume

Chapter four outlined some of the numerous studies that have documented a positive relationship between analysts' output and future abnormal returns and volume. The value and impact of brokers' output is analysed by measuring the relation between ratings and future abnormal returns and volume. In order to evaluate whether analysts add incremental value the relationship between each of the firm-specific variables and returns and volume is also examined.

Market-adjusted returns (R_{it}-R_{mt}) over the three and six months following the quarter end are calculated in order to assess the abnormal returns to each quintile[95]. These are labelled **RET(3)** and **RET(6)**, respectively, and are calculated using the approach detailed in equation 5.14, with returns running from week one to week 13 and 26 for three- and six-month returns, respectively.

If brokers exhibit a strong tendency to favourably recommend low (high) volume stocks then measuring future volume relative to the previous three quarters would overstate (understate) the volume impact of brokers' recommendations. Hence, abnormal volume for the next quarter, **VOL(F)**, is estimated by scaling the average weekly volume for each stock

[95] The results are robust to the use of the market model and CAPM. The role of risk is less important over relatively short event windows, as outlined in section 3.4.

subsequent to the end of the previous quarter by the average volume of the three quarters preceding the recommendation quarter.

$$VOL(F)_{it} = \frac{V_{it+1}}{\frac{1}{3}(V_{it-1} + V_{it-2} + V_{it-3})} \qquad (5.20)$$

5.5 Limitations

There are a number of limitations to the methodology adopted in this chapter. All event studies suffer from the joint-hypothesis problem, as they represent joint tests of market efficiency and the return-generating models employed to estimate abnormal returns. Although, this problem is mitigated by employing three models, it is unlikely that any of the models perfectly capture expected returns.

The relatively small number of companies on the Irish market represents another potential limitation. This problem is accentuated by the dominance of a small number of companies. Furthermore, the data collected from One Banker specifies the output of each broker at the end of each week. Thus, it is not possible to identify the exact date of each initiation and revision. Accordingly, the designation of week 0 for estimating abnormal returns and volume is somewhat arbitrary. However, the severity of this problem diminishes significantly as the test period increases. Finally, the data on brokers' output relates to brokerage houses; there is no data on the recommendations of individual brokers.

Chapter Six

Momentum and Reversal Findings and Discussion

6.1 Introduction

This chapter summarises the key findings relating to the contrarian and momentum strategies in the four markets under review. The remainder of this chapter is organised as follows. Section 6.2 presents the key findings pertaining to the two strategies in the main data period (1989-2006); alternative strategies based on various rank and holding periods and portfolio sizes are examined in section 6.3. Seasonal effects are discussed in section 6.4 and the robustness of the findings is examined in section 6.5 in the form of out-of-sample testing and analysis by period and firm. Conclusions are drawn in section 6.6.

6.2 Results

This section presents the findings pertaining to both strategies for the main data period (1989-2006) using the three models discussed in section 5.3. To begin with, the customary three- and one-year holding periods are used for the contrarian and strength rule strategies respectively, in order to get a broad picture of the underlying pattern of returns. Subsequently, more bespoke rank and holding periods and hybrid strategies are examined in light of previous findings that momentum is present for three months to one year before return reversals occur. The use of portfolios with extreme winners and losers is also examined.

Table 6.1 presents the returns to the two strategies for the four markets analysed. The results are obtained using the three models discussed in section 5.3 and are the average cumulative abnormal returns of five (17) holding periods for the contrarian (strength rule) strategy over the period 1989-2006. The period 2007-09 is reserved to test the out-of-sample validity of the results in section 6.5.

Table 6.1

Returns to contrarian investment and strength rule strategies (1989-2006)

Panel A reports the average returns to the contrarian investment strategy for the four countries and three models (as discussed in section 5.3). The figures reported are the average cumulative excess abnormal returns ($\overline{CAR}_L - \overline{CAR}_W$) of the five non-overlapping three-year holding periods (1992-94, 1995-97, 1998-00, 2001-03, 2004-06). Panel B reports the equivalent figures for the strength rule strategy, which are the average cumulative abnormal returns of the 17 non-overlapping one-year holding periods (1990 to 2006 inclusive). The figures in parentheses are the t-statistics, which are estimated using the methodology of De Bondt and Thaler (1985), with four and 16 degrees of freedom for the contrarian and strength rule strategies, respectively.

Panel A: Contrarian strategy

Model	Ireland	Greece	Norway	Denmark
Adjusted Mkt. Model	-0.152	0.331**	0.109	0.050
	(-0.77)	(2.35)	(0.42)	(0.27)
Market Model	0.074	0.520**	0.281	0.215***
	(0.41)	(3.62)	(1.10)	(1.65)
CAPM	-0.231	0.370	0.313	0.031
	(-1.40)	(0.88)	(1.46)	(0.18)

Panel B: Strength rule

Model	Ireland	Greece	Norway	Denmark
Adjusted Mkt. Model	0.070**	-0.093***	0.049	0.008
	(1.77)	(-1.71)	(0.71)	(0.18)
Market Model	0.016	-0.194**	0.035	0.009
	(0.35)	(-3.29)	(0.52)	(0.18)
CAPM	0.052	-0.106	0.004	0.026
	(1.03)	(-0.48)	(0.02)	(0.47)

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

The contrarian investment strategy generates positive excess abnormal returns in all countries except Ireland. This provides further out-of-sample confirmation of the findings of De Bondt and Thaler (1985). The highest returns are generated in Greece, which is the only market with statistically significant returns at the five per cent level. There are also economically significant returns in Norway, with more modest returns generated in Denmark. The contrarian investment strategy generates negative returns in Ireland as there is continuation of past returns. Such momentum in Irish returns can be seen over a one-year holding period in panel B. The positive strength rule returns in Ireland directly contradict the findings of O'Sullivan and O'Sullivan (2010) and O' Donnell and Baur (2009).

The excess abnormal returns in Greece are significantly larger than the 24.6% reported by De Bondt and Thaler (1985) for the US using the adjusted market model. The results confirm the findings of Richards (1997), who reports that in a 16-market study the largest reversals are observed in Denmark and Norway (23.5% and 16.8% respectively).

Contrarian returns in Greece become statistically insignificant when the CAPM is used. The returns remain economically significant but are considerably lower than market model abnormal returns. The average beta of losers increases by 27% between the rank and holding period, whereas that of the winners is relatively constant. However, the difference in mean betas is not statistically significant ($t = 1.39$). This suggests that risk accounts for some, but not all, of the excess abnormal returns found in Greece. This result partially confirms the finding of Antoniou *et al.* (2006a) that abnormal returns are insignificant in Greece when time-varying risk measures are employed. Contrarian returns are also less economically and statistically significant in Denmark when the CAPM is employed.

In contrast, abnormal contrarian returns in Norway increase monotonically with model sophistication in contrast to the findings of Chan (1988), who argues that the beta of losers (winners) should increase (decrease) between the rank and holding period, thus reducing returns when the CAPM is used. In Norway the average beta of losers decreases marginally, while that of the winners remains stable. This is consistent with the findings of De Bondt and Thaler (1985), who report statistically significantly larger betas for winners than losers.

The statistically significant negative strength rule returns in Greece add further weight to the evidence of return reversals. One-year holding periods are typically associated with return continuation. However, such is the pervasive nature of reversals in Greece that past losers outperform past winners over one-year holding periods. Excess abnormal strength rule returns are not statistically significant in the other two markets, although returns are economically significant in Norway using two of the three models. The lack of statistically significant positive momentum returns in Greece, Norway, and Denmark contradicts studies such as Liu *et al.* (2011); Naranjo and Porter (2007); Griffin *et al*. (2005); Doukas and McKnight (2005); and Rouwenhorst (1998), as detailed in table 2.1. Figure 6.1 presents the evolution of cumulative excess abnormal returns over the holding periods for each strategy[96].

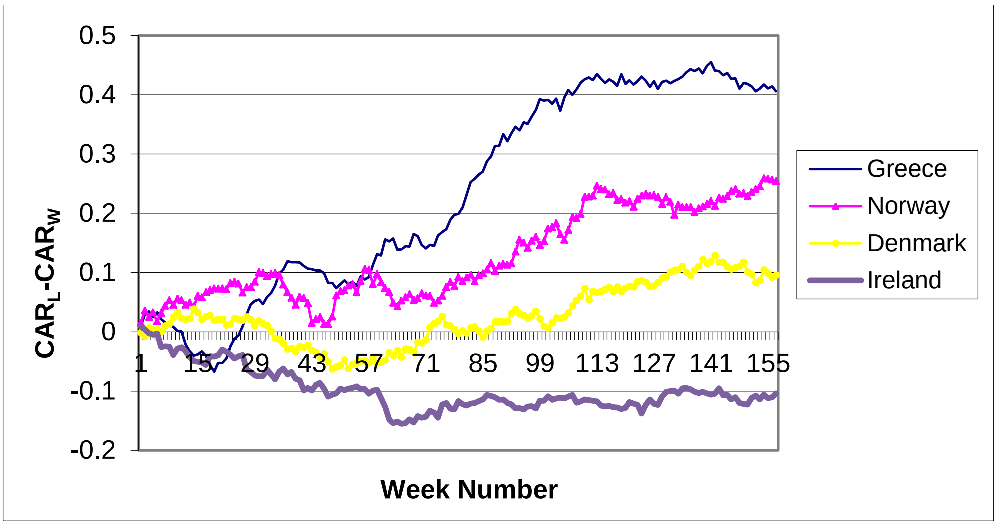
[96] For ease of interpretation, the order of the legend in each graph coincides with the order of the lines at the *end* of the time period.

Figure 6.1

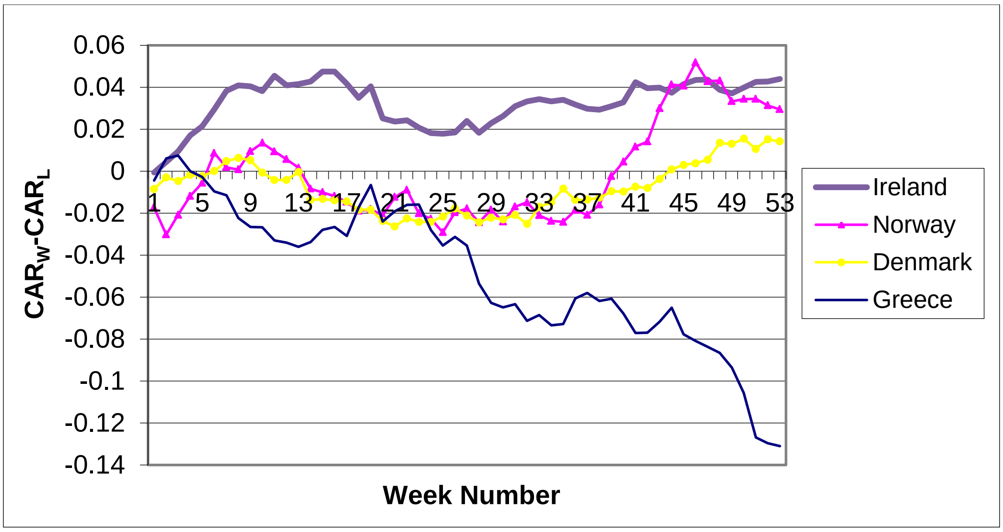
Average excess abnormal returns (1989-2006)

The chart plots the cumulative excess abnormal returns for each market for the contrarian (panel A) and strength rule strategies (panel B). Each line is the cumulative average contrarian (momentum) returns over five (17) holding periods and three return-generating models.

Panel A: Contrarian strategy



Panel B: Strength rule strategy



There are two important points to bear in mind when analysing the above findings. First, the figures ignore transaction costs. As stated previously the strategies are self-financing; thus, only round-trip transaction costs merit consideration. It is assumed that excess abnormal returns of 2% per annum are sufficient to cover transaction costs. Second, the contrarian returns are earned over a three-year period; thus annualised returns are presented in table 6.2 in order to facilitate a direct comparison with the strength rule returns[97].

Table 6.2

Average annualised returns to contrarian investment strategy

The table reports the average annualised excess abnormal returns to the contrarian investment strategy ($\overline{CAR}_L - \overline{CAR}_W$) for the five non-overlapping three-year holding periods.

Model	Ireland	Greece	Norway	Denmark
Adjusted Mkt. Model	-0.053	0.100	0.035	0.016
Market Model	0.024	0.150	0.086	0.067
CAPM	-0.084	0.111	0.095	0.010

In annualised terms, the average abnormal returns of Greece and Norway are economically significant, while it seems unlikely that the returns in Denmark would be sufficient to cover moderate transaction costs for two of the three models. The returns to the strategy in Greece are striking, with double-digit average annualised returns using all three models. The results suggest that reversals are not evident in Ireland. Accordingly, the analysis pertaining to return reversals in the remainder of this chapter is limited to the other three markets; whereas strength rule returns are examined for Ireland.

The returns in table 6.1 may not accurately reflect the profits available to many investors as both strategies involve short-selling. Barber and Odean (2008) find that only 0.29% of individual traders take short positions. However, this does not necessarily imply that small investors cannot take advantage of return continuation and reversal. Table 6.3 details the contribution of the winner and loser portfolios to the overall excess abnormal returns detailed earlier.

[97] Annualised returns (r_a) are obtained using the formula $r_a = (1+r_t)^{1/3}-1$, where r_t is the three-year return.

Table 6.3

Contribution of winner and loser portfolios

The table presents the contribution of the winner and loser portfolios to overall excess abnormal returns (t-statistics in parentheses). The returns for each model represent the average of five (17) holding periods for the contrarian (strength rule) strategy. For the contrarian strategy, the returns in the winner column are the negative of the winner returns as the contrarian strategy (Greece, Norway, and Denmark) involves short-selling past winners. The opposite is true for strength rule returns (Ireland).

	$\overline{CAR}_L$	$\overline{CAR}_W$	**Excess**
Ireland			
Adjusted Market Model	0.025	0.045***	0.070**
	(0.83)	(1.56)	(1.77)
Market Model	0.017	-0.001	0.016
	(0.47)	(-0.02)	(0.35)
CAPM	-0.003	0.055**	0.052
	(0.08)	(1.75)	(1.03)
Greece			
Adjusted Market Model	0.359**	-0.028	0.331**
	(3.12)	(0.35)	(2.35)
Market Model	0.231***	0.289*	0.520**
	(1.76)	(4.91)	(3.62)
CAPM	0.557	-0.187	0.370
	(1.51)	(0.93)	(0.88)
Norway			
Adjusted Market Model	0.045	0.063	0.109
	(0.19)	(0.73)	(0.42)
Market Model	0.114	0.167	0.281
	(0.50)	(1.47)	(1.10)
CAPM	0.363***	0.050	0.313
	(2.02)	(0.43)	(1.46)
Denmark			
Adjusted Market Model	0.103	-0.053	0.050
	(0.65)	(-0.57)	(0.27)
Market Model	0.140**	0.074	0.215***
	(2.45)	(0.64)	(1.65)
CAPM	0.031	0.001	0.031
	(0.28)	(0.01)	(0.18)

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

It is clear that the loser portfolio dominates in all three countries with return reversals. On average, the loser portfolio accounts for approximately 88% of the excess abnormal returns. This is similar to the equivalent figure of 80% reported by De Bondt and Thaler (1985) for three-year rank and holding periods. If the contrarian investment strategy returns are due to overreaction then this suggests that investors overreact to bad news to a greater degree than they do for good news. Table 6.3 shows that it is possible for an investor to generate significant returns even if they cannot engage in short-selling. This is of particular importance, as restrictions or bans were been placed on short selling in all four markets in the aftermath of the eurozone crisis. A strategy of buying past losers would generate average abnormal returns of 38.2, 17.4 and 9.1% in Greece, Norway, and Denmark respectively. Such a strategy would also reduce transaction costs by eradicating the need for costly short-selling.

The same is true of the strength rule strategy in Ireland, where the winner portfolio contributes approximately 72% to the average excess abnormal returns of 4.6%. An investor without the ability to short sell could generate excess abnormal returns of 3.3% by simply buying past winners. This finding contrasts with the assertion of Hong *et al.* (2000) that the majority of the profits to the momentum strategy arise from selling the past losers. However, it is consistent with previous findings pertaining to Ireland. Recall that O' Donnell and Baur (2009) show that a strategy of buying past winners alone yields economically and statistically significant abnormal returns.

6.3 Alternative specifications

This section examines variations of the contrarian and strength rule strategies along two dimensions. The first approach examines rank and holding periods of various lengths, following approaches similar to De Bondt and Thaler (1985) and Jegadeesh and Titman (1993). The second alternative specification varies the number of stocks in the winner and loser portfolio, as abnormal returns are frequently shown to be more pronounced for stocks experiencing extreme past returns (see, for example, De Bondt and Thaler, 1985).

6.3.1 Alternative rank and holding periods

The contrarian returns in the previous section are derived using a three-year rank and holding period, as originally employed by De Bondt and Thaler (1985). It is of interest to examine alternative rank and holding periods, as panel A of figure 6.1 presents evidence of continuation followed by reversal. Table 6.4 presents the average monthly excess abnormal contrarian returns for a number of alternative rank and holding periods ranging from six to 36 months[98].

Twelve-month rank periods generate economically significant abnormal returns in Greece and Norway over long holding periods. Furthermore, six-month rank periods generate economically and statistically significant abnormal returns in Greece for all holding periods of at least 12 months. These results contrast starkly with the results of De Bondt and Thaler (1985), who report that there is no reversal for one-year portfolio formation periods in the US. The positive, albeit statistically insignificant, abnormal returns to the 6,6 strategy contradict the findings of Van der Hart *et al.* (2003), who report that a 6,6 momentum strategy generates abnormal returns of 0.91% per month. There is evidence of short-term reversals in Norway, with significant abnormal returns to six-month holding periods[99].

[98] For the sake of brevity the table reports excess abnormal returns derived from the market model. The results are broadly similar for all three models.

[99] The majority of alternative rank and holding periods generate insignificant or negative abnormal returns in Denmark as a result of return continuation in the first year of the holding period. The 36,36 strategy, which generates 0.54% per month (t = 1.65), is the only combination of rank and holding periods with economically significant excess abnormal returns.

Table 6.4

Alternative contrarian returns

The table presents the average monthly excess abnormal contrarian returns ($\overline{CAR}_L - \overline{CAR}_W$) for a number of alternative rank and holding periods ranging from six to 36 months. The returns are based on equally-weighted portfolios of market model returns. One-tail t-statistics are reported in parentheses.

Rank period (months)	**Holding period (months)**					
	6	**12**	**18**	**24**	**30**	**36**
Greece						
6	0.92	1.71**	1.48**	1.35**	1.21**	0.92**
	(1.19)	(3.19)	(2.53)	(2.13)	(3.16)	(3.09)
12	-0.71	0.62	0.53	0.70	0.57	0.32
	(-0.59)	(1.03)	(0.88)	(0.89)	(1.19)	(0.88)
18	1.17	0.85***	0.82	0.99	0.84***	0.61**
	(1.40)	(1.63)	(1.43)	(1.31)	(2.04)	(2.21)
24	0.54	0.70	1.14***	1.04	0.99**	0.75**
	(0.64)	(1.25)	(1.98)	(1.40)	(2.52)	(2.79)
30	0.70	0.65	1.12***	1.30***	1.10**	0.88**
	(1.04)	(1.18)	(1.82)	(1.73)	(2.68)	(3.06)
36	0.75	1.10**	1.42**	1.72***	1.40**	1.17**
	(1.15)	(2.19)	(2.27)	(2.12)	(2.94)	(3.62)
Norway						
6	1.72*	0.41	0.19	0.16	0.31	0.32
	(2.67)	(0.35)	(0.24)	(0.18)	(0.39)	(0.45)
12	0.80	-0.27	-0.23	0.37	0.45	0.45
	(0.89)	(-0.22)	(-0.28)	(0.42)	(0.56)	(0.61)
18	0.10	0.02	0.05	-0.15	0.04	0.24
	(0.15)	(0.02)	(0.06)	(-0.18)	(0.06)	(0.4)
24	1.26**	0.71	0.48	0.54	0.65	0.66
	(1.79)	(0.67)	(0.69)	(0.66)	(1.01)	(1.13)
30	1.07**	0.21	0.00	0.13	0.36	0.37
	(1.75)	(0.19)	(0)	(0.15)	(0.51)	(0.57)
36	1.08	0.83	0.47	0.62	0.68	0.69
	(1.16)	(0.76)	(0.66)	(0.8)	(1.01)	(1.1)

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

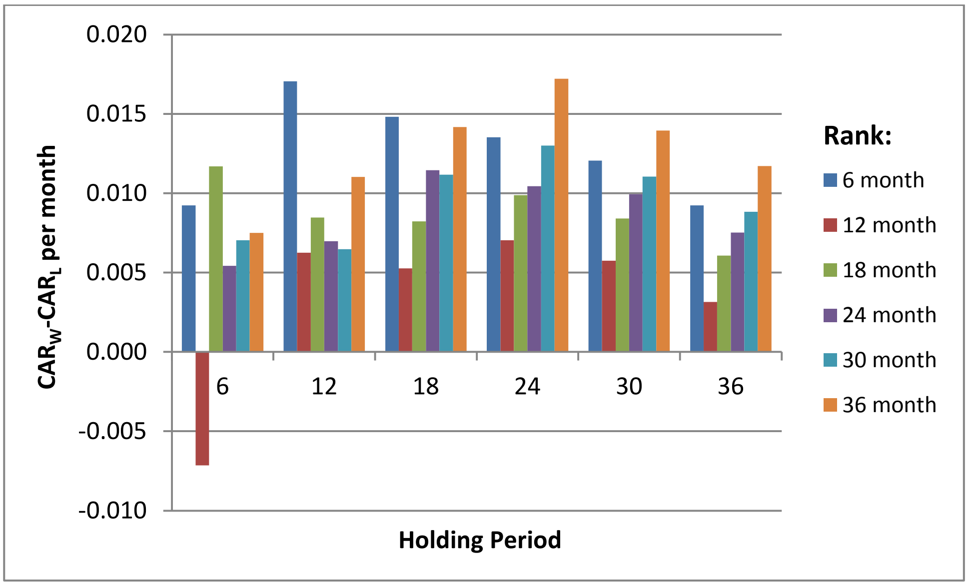
Figure 6.2 presents the abnormal returns for the various rank and holding period combinations in Greece and Norway.

Figure 6.2

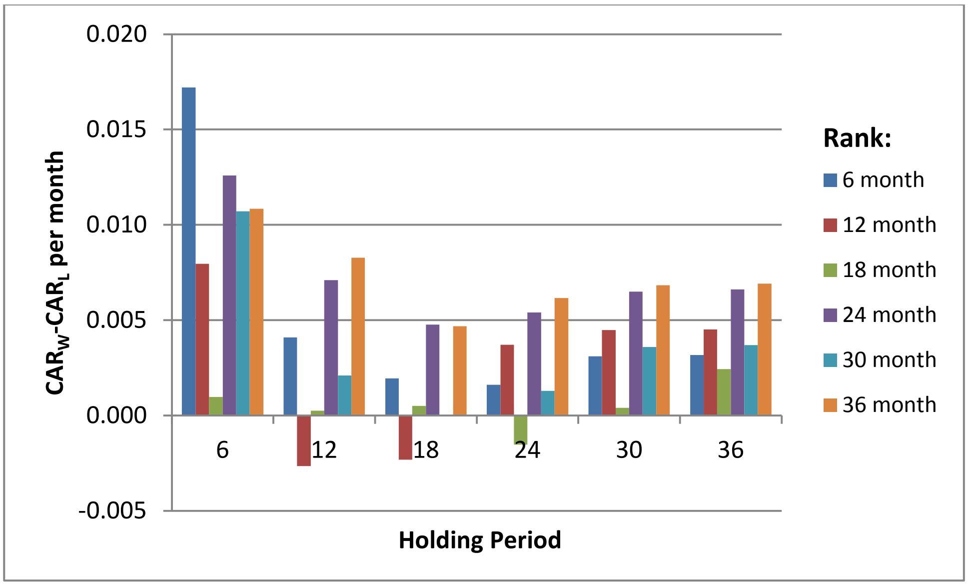
Returns to alternative rank and holding period strategies

The charts present the average monthly market model excess abnormal contrarian returns $(\overline{CAR}_L - \overline{CAR}_W)$ for a number of alternative rank and holding periods ranging from six to 36 months for Greece (panel A) and Norway (panel B).

Panel A: Greece



Panel B: Norway



It can be seen that the increase in average monthly returns in Greece with longer rank periods would be monotonic in many instances if not for the high returns to the strategies based on six-month rank periods. The returns to six-month rank periods decrease monotonically for holding periods of 18 months or beyond. Returns also tend to increase with longer holding periods. However, 36-month holding periods are sub-optimal.

The hitherto analysis has examined rank and holding periods of differing lengths. However, each strategy commenced one week after the end of the rank period. Figure 6.1 suggests that this may not be optimum as continuation followed by reversal is evident in two of the three markets (Greece and Denmark). Abnormal returns are economically significant in year two in all three markets. This is consistent with the findings of De Bondt and Thaler (1985), who report abnormal returns in each of the three holding years of 5.4, 12.7, and 6.5%, respectively.

Contrarian returns in Greece are 8.0, 31.6, and 1.1% respectively in years one, two and three. However, the strategy generates negative or insignificant abnormal returns in the first six months of year one due to continuation followed by reversal. It thus appears that the optimum strategy in Greece would involve skipping the first six months of the holding period. In order to maximise annualised returns it is also advisable to omit the third year of the holding period, where abnormal returns are insignificant. This alternative contrarian strategy generates average excess abnormal returns of 38.7% over the 18-month holding period, which is the equivalent of 1.83% per month. The relatively poor performance of the strategy in year three represents further evidence of reversal, as the superior performance of the erstwhile losers itself begins to reverse.

The contrarian strategy generates a significant loss in year one in Denmark, suggesting that investors could profit from a hybrid strategy, which profits from the observed pattern of continuation followed by reversal by engaging in strength-rule trading in year one and contrarian trading in years two and three. Such a hybrid strategy generates average abnormal returns of 34% (1.22% per month). The standard three-year holding period is optimum in

Norway as the contrarian strategy generates consistent and significant positive excess abnormal returns in each of the three holding years.

Alternative holding periods for the strength rule strategy are motivated by the approach of Jegadeesh and Titman (1993), who examine 16 strategies based on combinations of rank and holding periods of three, six, nine, and 12 months[100]. The principal focus here is on returns for Ireland as strength rule returns were not statistically significant in the other three markets. Table 6.5 reports the average monthly strength rule returns for ranking and holding periods ranging from three to 12 months in Ireland. With space considerations in mind, the table details the excess abnormal returns derived from the CAPM. The results are broadly similar for the other two models.

Table 6.5

Alternative strength rule returns

The table presents the average monthly excess abnormal strength rule returns for a number of alternative rank and holding periods ranging from three to 12 months. The returns are based on equally-weighted portfolios of CAPM returns. One-tail t-statistics are reported in parentheses.

	Holding period (months)			
Rank period (months)	**3**	**6**	**9**	**12**
3	1.21**	0.11	0.04	0.33
	(1.83)	(0.27)	(0.10)	(0.81)
6	1.52**	0.36	0.30	0.32
	(2.46)	(0.83)	(0.62)	(0.79)
9	2.04*	0.74**	0.58***	0.52***
	(3.56)	(1.95)	(1.34)	(1.36)
12	1.09**	0.05	0.03	0.14
	(1.80)	(0.14)	(0.07)	(0.35)

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

[100] Jegadeesh and Titman (1993) examine an additional 16 strategies where a week is skipped between the rank and holding period. The results for Ireland in this study are virtually identical when this approach is adopted. Therefore, such results are not reported for every holding period.

The 9,3 (rank, hold) strategy is optimum, generating average returns of 2.04% per month when the CAPM is employed[101]. It thus appears that momentum in Irish returns is largely a short- to medium-term phenomenon. The returns to the 9,3 strategy are consistent, with positive excess abnormal returns in more than three-quarters of the three-month holding periods.

These results provide further out-of-sample confirmation of the findings of Jegadeesh and Titman (1993) and Rouwenhorst (1998), which show that 9,3 strategies are profitable. However, both studies find that the 12,3 strategy is optimum, with average monthly returns of 1.31% and 1.35% respectively.

The breakdown of abnormal returns by portfolio contrasts with the findings of Jegadeesh and Titman (1993) and Rouwenhorst (1998) in one important respect. In those two studies the winner and loser portfolios generated positive abnormal returns for every rank and holding period combination. Thus, a strategy of simply buying past winners would have generated larger abnormal returns.[102] In contrast, the evidence of underreaction in this study is more symmetrical, as the loser portfolio generates negative abnormal returns for 11 of the 16 rank and holding period combinations. This appears to contradict the findings of McQueen *et al.* (1996) and Ashley (1962) that stocks react slowly to good news but quickly to bad news. The winner portfolio accounts for approximately 84% of the abnormal returns. Thus, short-selling constraints cannot explain the persistence of such anomalous returns.

Consistent with Jegadeesh and Titman (1993) and Rouwenhorst (1998), the economic and statistical significance of average monthly returns generally increases with shorter holding periods and longer rank periods. This pattern can be seen in figure 6.3. Three-month holding periods and nine-month holding periods are optimum for all combinations; whereas 12-month rank periods generate the lowest abnormal returns for all holding periods. The profitability of momentum strategies with relatively short holding periods also confirms the results of

[101] The average returns for the 9,3 strategy using the market model and adjusted market model are 1.81% (t = 3.37) and 1.98% (t = 3.56) respectively.

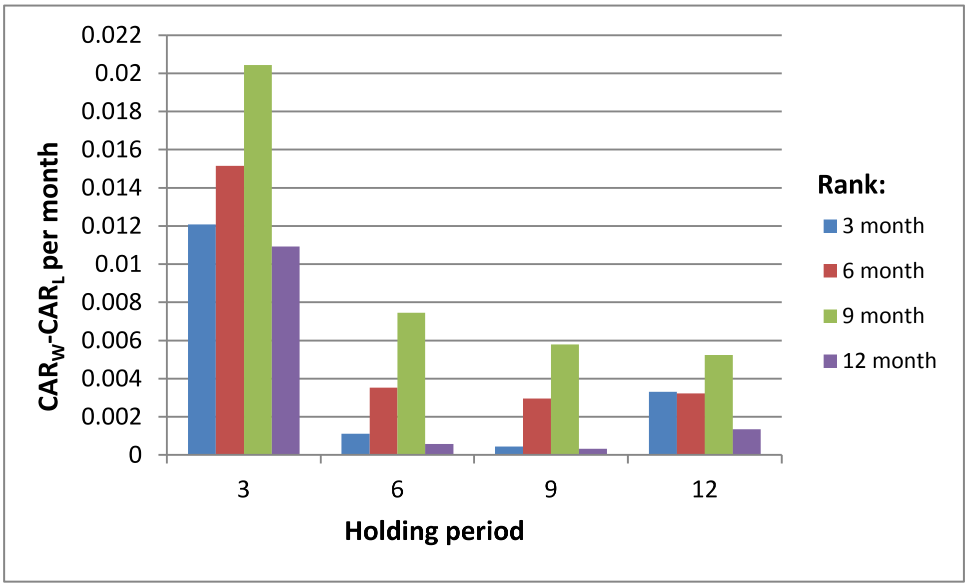
[102] It seems that the only advantage of short selling past losers is that the strength rule strategy becomes self-financing.

Naranjo and Porter (2007), who find that a momentum strategy based on 11-month rank periods and one-month holding periods generates an average of 1.01% per month in Ireland.

Figure 6.3

Returns to alternative rank and holding periods

The chart shows the average monthly excess abnormal returns to the strength rule strategy in Ireland ($\overline{CAR}_W - \overline{CAR}_L$) for the 16 rank and holding period combinations using the CAPM.



The results are consistent with the findings of O'Sullivan and O'Sullivan (2010), who report that momentum returns in Ireland are smaller for shorter ranking periods. However, they contrast with the results of O' Donnell and Baur (2009), which state that the most successful momentum strategy involves ranking stocks over the past six months and holding the winners for the subsequent 12 months. Furthermore, O' Donnell and Baur (2009) find that the 9,3 strategy is the least successful of all rank and holding period combinations.

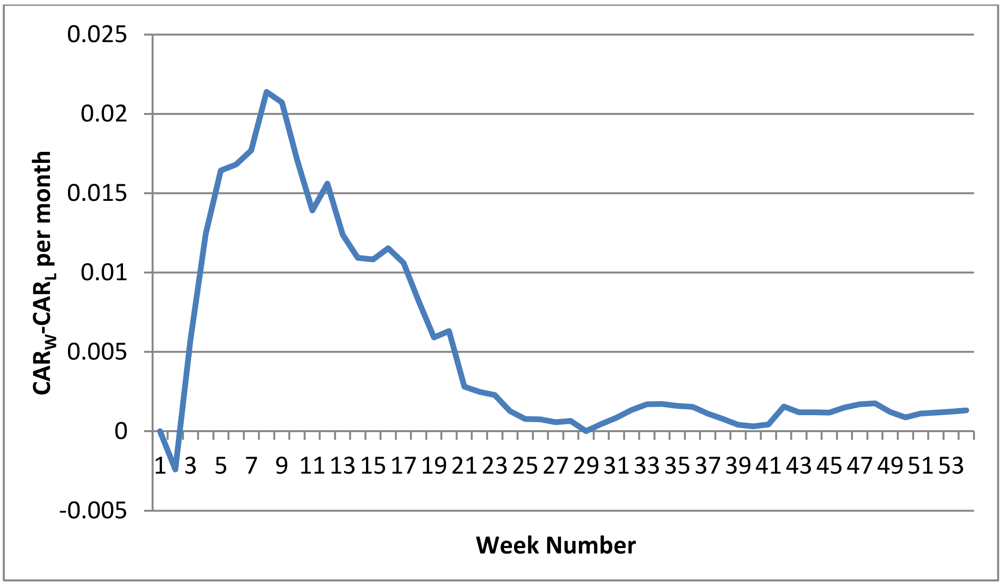
The higher average monthly returns to shorter holding periods suggest that underreaction is corrected in the short- to medium-term. The superiority of longer ranking periods may arise as short-term periods contain a larger noise component. These findings imply that momentum is largely exhausted after approximately 12 months. If underreaction is the principal cause of return continuation then this suggests that it takes 12 months for prices to fully incorporate the economic impact of news.

The superiority of three-month holding periods is consistent with figure 6.1, where cumulative excess abnormal returns in Ireland increase quickly over the first two months of the year, after which the rate of increase subsides. Table 6.5 uses the framework of prior studies to assess alternative rank and holding periods at four three-month intervals. It is unlikely that the optimum holding period coincides with one of these intervals. Figure 6.4 presents average monthly returns on a continual basis in order to provide a more complete picture of the optimum holding period.

Figure 6.4

Average monthly momentum returns (Ireland)

The chart plots the average monthly returns for Ireland using a nine-month rank period and holding periods ranging from one week to one year. The returns are excess abnormal returns generated using the market model.



A holding period of approximately seven weeks is optimum, with average monthly returns of 2.1%, rising to 2.54% when a week is skipped between the holding and rank period[103]. Although Jegadeesh and Titman (1993) recommend skipping a week to minimise microstructure biases, it also has the effect of increasing average monthly returns for the majority of the 16 strategies that they examine. The same effect is observed in this study due to the negative strength rule returns in week one. It is noteworthy that even the least effective holding periods generate abnormal returns in excess of 0.5% per month.

The returns to alternative rank and holding periods in Greece are also of interest given the statistically significant negative returns to the strength rule on the Greek market. Such evidence is consistent with short-term reversals and reinforces the patterns presented in table 6.4 relating to longer holding periods. The 12,3 contrarian strategy in Greece would generate average excess abnormal returns of 1.21% per month. It is interesting to note that the economic and statistical significance of average monthly returns increase as the holding period increases. This is the opposite of the findings in relation to continuation and suggests that overreaction is corrected in a more delayed fashion. Average monthly abnormal momentum returns are insignificant in the other two markets, regardless of the rank and holding period utilised.

6.3.2 Portfolio size

De Bondt and Thaler (1985) find that reversals are more pronounced for stocks with extreme past performance. The benefits of using extreme stocks may be twofold to an investor, as doing so could simultaneously increase returns and decrease transaction costs[104]. This supposition is tested by altering the number of winner and loser stocks held for the three markets that displayed evidence of reversal. The average number of stocks held in each portfolio in the original dataset was 11. The relatively small number of stocks listed in the four markets studied renders the use of deciles impractical. Instead, portfolios of extreme

[103] The average monthly returns to the strategy using nine-month rank periods and seven-week holding periods are 2.57% and 2.56% for adjusted market model and CAPM respectively.

[104] However, it should be noted that the use of extreme stocks will typically be accompanied by an increase in the variance of portfolio returns.

stocks are formed with either four or two extreme winners and losers. The returns to these alternative specifications are presented in table 6.6.

Table 6.6

Returns to portfolios of varying sizes

The table compares the returns to the strength rule (Ireland) and contrarian investment strategy (Greece, Norway, and Denmark) using portfolios of varying sizes. The column labelled 'various' contains the returns as discussed in section 6.2, where the top (bottom) half of stocks are labelled winners (losers). The middle stock is omitted in cases where there is an odd number of stocks and the number of stocks in each portfolio ranges from six to 15, with an average of 11. The last two columns present the returns when the extreme four or two stocks are held in each portfolio. Each figure is the average excess abnormal return of five holding periods with t-statistics in parentheses.

		Number of shares in each portfolio		
Country	**Model**	**Various**	**Four**	**Two**
Ireland	Adj. MM.	0.070**	0.060	0.039
		(1.77)	(0.71)	(0.28)
	MM	0.016	-0.021	0.058
		(0.35)	(-0.24)	(0.47)
	CAPM	0.052	0.108	0.076
		(1.03)	(1.45)	(0.62)
Greece	Adj. MM.	0.331**	0.520**	0.645**
		(2.35)	(2.79)	(2.27)
	MM	0.520**	0.721**	1.014*
		(3.62)	(3.71)	(4.92)
	CAPM	0.370	0.439	0.556
		(0.88)	(1.00)	(1.28)
Norway	Adj. MM.	0.109	0.471**	0.600
		(0.42)	(2.39)	(1.64)
	MM	0.281	0.597	0.689**
		(1.10)	(2.81)	(2.79)
	CAPM	0.313	0.501**	0.859**
		(1.46)	(2.83)	(2.79)
Denmark	Adj. MM.	0.050	0.122**	-0.044
		(0.27)	(2.23)	(-0.48)
	MM	0.215	0.288**	0.413**
		(1.65)	(2.77)	(2.78)
	CAPM	0.031	0.206**	0.021
		(0.18)	(2.33)	(0.33)

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

The pattern of returns in table 6.6 generally confirms the stylised finding of previous research that reversals are more pronounced for firms with more extreme past price movements. In the case of Greece, returns increase monotonically with the use of more extreme stocks. The average return increases from 41% when all stocks are used, to 57% and 74% when four and two stocks are used in each portfolio, respectively. The prospect of making a 74% excess abnormal return by buying two shares and short-selling two shares should be particularly appealing to small investors. It also suggests that fund managers should focus on a small number of extreme stocks (ignoring diversification benefits).

The excess abnormal returns increase to an average of 66.8% when the first six months and last year of the three year test period are skipped and each portfolio contains two stocks. This is the equivalent of 2.76% per month over the modified 18-month holding period. Implementing the contrarian strategy in the second year alone on such extreme stocks would generate abnormal returns of 55.2% (3.73% per month).

A similar pattern is uncovered in Norway where excess abnormal returns increase from 25% to 53% and 72% when four and two stocks are respectively used in each portfolio. The results for Denmark are less emphatic, which is not surprising as there is less evidence of return reversals in Denmark. The general tendency is for returns to increase as more extreme stocks are used but they do not increase with same monotonic regularity as with Greece and Norway. Returns increase using all three models when moving to four stocks per portfolio. All of the above contrarian strategies remain profitable after the omission of the winner returns and cannot thus be explained by short-selling constraints.

The increase in returns in Ireland is not as consistent and significant as is the case for the contrarian strategies in the other three markets. Indeed, the use of extreme stocks results in lower momentum returns to the 9,3 strategy. This is not surprising as, *ceteris paribus,* one would expect that the prices of stocks with extreme past performance are more likely to be nearer their turning points than other stocks. Mean reversion implies that reversals may be more likely than continuation for such stocks. In other words, it is more plausible to expect that the prices of extreme stocks have overreacted rather than underreacted. This finding is consistent with O'Sullivan and O'Sullivan (2010), who report that momentum returns in Ireland are smaller for portfolios of extreme stocks.

The above results show that there is considerable structure in share price returns in three of the four stock markets. Of course, an investor would not know the optimum holding period and portfolio size *ex ante*. The out-of-sample forecasting period (2007-09) is used to test the robustness of the optimum strategies for each market. The results of these tests are presented in section 6.5.1.

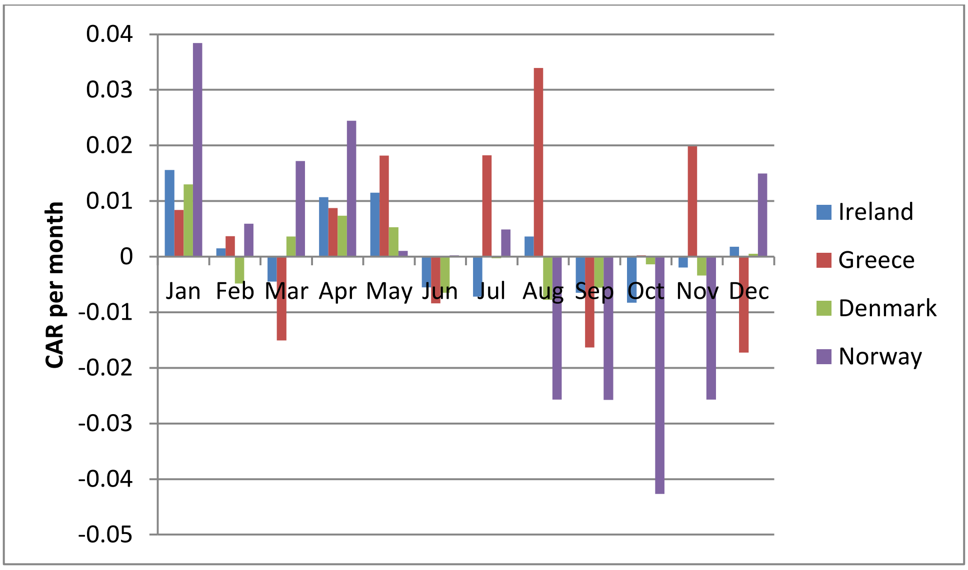
6.4 Seasonal effects

This section examines the seasonality of any abnormal returns in order to ascertain whether such returns are merely a manifestation of another effect, such as the January effect. Of course, an investor is not too concerned whether any returns are caused by overreaction, mean reversion, the January effect, or any other effect. However, for academics it is important to understand the source of any anomalous returns. Before examining the role of seasonal patterns in explaining anomalous returns a general flavour of any seasonal patterns is gauged by charting monthly aggregate returns in figure 6.5.

Figure 6.5

Average aggregate monthly abnormal returns

The graph shows the average monthly abnormal returns for all stocks over the period 1990-2006. The data is calculated by taking the average return of all stocks in the strength rule holding periods. The results are almost identical when the contrarian periods are used.



A number of important seasonal patterns are evident. First, January returns are positive in all four markets. This pattern is particularly systematic in Ireland and Norway, where January returns are positive in 14 of the 17 holding periods. The equivalent figures for Greece and Denmark are eight and 12 respectively. Possible explanations for this are examined shortly in the context of both anomalies. In general, the observation that abnormal returns are negative in only one of the four markets in December suggests that this seasonality is not caused by tax-loss selling or window dressing.

Second, returns are positive in April and May and negative in September in all four markets. It is difficult to furnish an intuitive explanation for this pattern of returns. Indeed, it is almost diametrically opposed to the pattern implied by the Halloween effect and its advice to 'sell in May and go away' (see, for example, Bouman and Jacobsen, 2002). Third, there are strong cyclical patterns in Norway with a systematic tendency towards positive (negative) returns in the first (second) half of the year. The most consistent seasonal trends in Norway are the negative returns in September and October, which both occur in 14 of the 17 holding periods.

It should be noted that the returns in the figure 6.5 are aggregate figures, while those of the two trading strategies under review are net figures (winners minus losers and *vice versa*). Accordingly, seasonalities may not manifest themselves in the returns to the two strategies if both winners and losers experience extreme performance in the same direction and of a similar magnitude. Alternatively, aggregate returns may understate the effect of seasonalities on anomalous returns if the returns to winners and losers are of the opposite sign. Figure 6.6 presents the average excess abnormal returns to the contrarian (panel A) and strength rule (panel B) strategies for each month.

It appears that the January effect partially explains the anomalous returns outlined in this chapter[105]. January returns are positive using contrarian rankings in the three markets that displayed return reversals (Greece, Denmark, and Norway) and using strength rule rankings in the market that exhibited continuation to the greatest extent (Ireland). January returns in Ireland, Greece, Denmark, and Norway account for 50, 18, 35, and 40% of anomalous returns respectively. However, in all four markets excess abnormal returns remain significant when January returns are omitted, suggesting that the two anomalies are distinct phenomena to the turn-of-the-year effect[106].

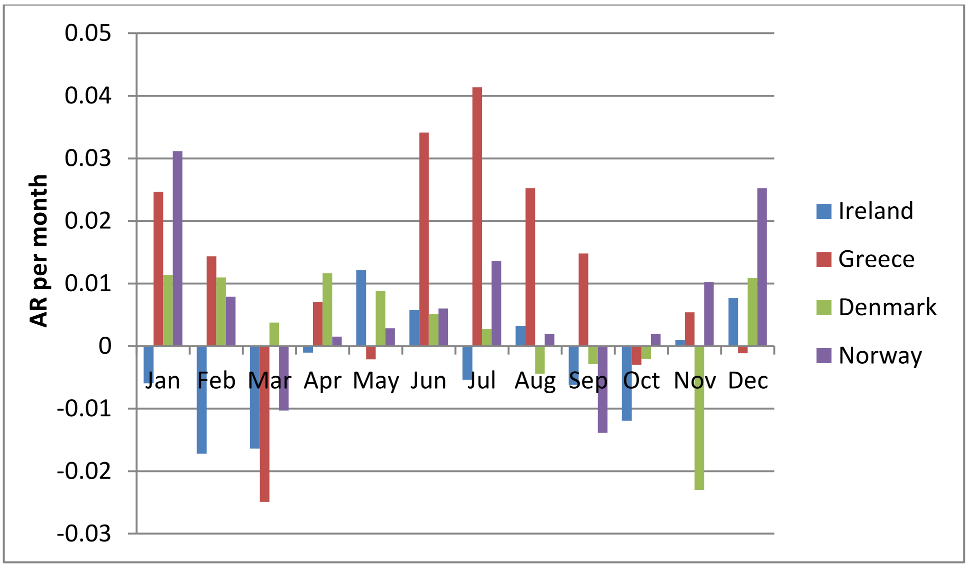
[105] Recall that it is expected that the January effect would be evinced by positive (negative) returns in January (December) for the contrarian strategy and *vice versa* for the strength rule if tax-loss selling or window dressing are the principal drivers of the January anomaly.
[106] For example, omitting January returns in Greece only reduces average monthly contrarian returns from 1.1% to 1% per month.

Figure 6.6

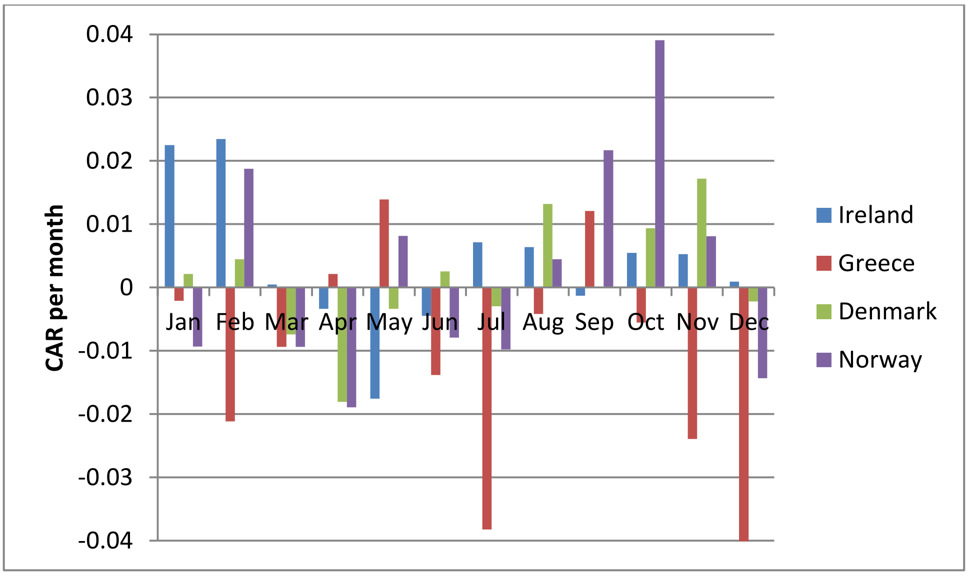
Average excess abnormal returns by month

The graphs present the average monthly returns throughout the year for the two strategies. Panel A presents the average abnormal returns of loser stocks minus that of past winners for each month of the year. Each figure is calculated as the average abnormal return for the relevant month over the 15 years of holding periods (1992-2006). Panel B presents the strength rule equivalent, based on winner-minus-loser returns using data from the 17 holding-period years (1990-2006). In both panels, the average abnormal returns of the three models are presented.

Panel A: Contrarian returns



Panel B: Strength rule returns



There are a number of monthly returns that stand out in the above graphs. However, there are relatively few instances where an average monthly return is significantly different to the average monthly return for the entire year. Table 6.7 presents details of such cases.

Table 6.7

Statistically significant monthly returns

The table presents the cases where average monthly abnormal returns are significantly different to average returns for the entire year using a two-tail t-test. The final column shows the percentage of holding periods where abnormal returns are of the same sign as the average return as presented in figure 6.6.

Market	Month	Strategy	Portfolio	Monthly return	t-statistic	%
Norway	October	Strength rule	Loser	-6.22	-2.52*	77
Norway	October	Strength rule	Winner-loser	3.91	1.76***	100
Norway	January	Contrarian	Loser	5.23	2.29**	100
Norway	January	Strength rule	Loser	4.31	1.94***	82
Norway	January	Strength rule	Winner	3.38	1.84***	82
Ireland	January	Strength rule	Winner	2.69	1.83***	88
Greece	March	Contrarian	Loser-winner	-2.49	-1.88***	60
Greece	March	Contrarian	Loser	-3.45	-2.29**	80

* Significant at the 2% level
** Significant at the 5% level
*** Significant at the 10% level

The most significant abnormal return is the 6.2% that the loser portfolio contributes to momentum returns in Norway in October. In most cases the winner and loser returns cancel each other out to some extent so that seasonal patterns do not permeate to the level of the excess abnormal returns. Indeed, there is no case where the excess abnormal returns are significantly positive at the five per cent level. Therefore, one can conclude that the anomalous returns presented in this chapter are more than mere manifestations of seasonal anomalies.

Perhaps the most striking seasonal pattern is the dramatic increase in excess abnormal returns in Greece in the middle third of the year. There is no apparent reason for this seasonality and it represents a potentially fruitful area for future research. However, contrarian returns in Greece remain significant after the omission of the returns from June-September.

The findings for Ireland are consistent with the results of Lucey and Whelan (2004), who report that returns are elevated in Ireland in January and April. The positive momentum returns in January are quite surprising as the tax-loss selling and window-dressing hypotheses imply that strength rule returns should be negative in January as explained in section 2.7.4. The positive abnormal returns of 2.25% in January are in sharp contrast with the negative returns of 7% and 5.85% reported in Jegadeesh and Titman (1993) and Grundy and Martin (2001), respectively. Remarkably, January abnormal returns for the winner portfolio are positive in 15 of the 17 holding periods.

However, the high January returns for the strength rule must be interpreted with caution vis-à-vis the tax-loss selling hypothesis. In 2002, the start of the tax year in Ireland was moved from April to January. Aggregate returns are elevated in April and May, implying that tax-loss selling may be driving seasonal returns. However, there are at least three reasons why this may not be the case.

First, January returns were higher prior to 2002 and are not statistically significant from 2002 onwards. Second, excess abnormal returns are of the opposite sign than expected in January pre-2002; the January effect would imply negative January returns to the strength rule as past losers outperform past winners. Excess returns are of the prescribed sign in April but are not statistically significant. Third, excess abnormal returns are close to zero in December. The tax-loss selling hypothesis suggests that returns at the end of the year should be positive for the strength rule, as investors sell past losers in order to realise tax losses.

The tax year commences in January in the other three markets. Thus, it is tempting to conclude that the high January contrarian returns are consistent with tax-loss selling. However, December returns are positive or close to zero in these markets, suggesting that there is no significant selling of past losers at the end of the tax year. The trivial December returns also invalidate the window-dressing explanation for the turn-of-the-year effect. If fund managers sold small stocks at the end of the year and re-purchased them at the beginning of January, one would expect to see a negative December effect.

The high strength rule returns in Ireland in January and February raise an important question. Are the large returns to the 9,3 strategy outlined in section 6.2.1 caused by short-term continuation or is it simply that the three-month holding period coincides with the beginning of the calendar year? To answer this question the strategy is re-examined with rank and holding periods, commencing in each month outside the first quarter. The findings show that abnormal returns are consistently large for all three-month holding periods. Thus, it seems that short-term continuation is a systematic feature of the Irish market and is not confined to the turn of the year.

In summary, the evidence of anomalous returns documented in this chapter cannot be explained by seasonal variations in returns. Although seasonal patterns exist in all four markets, excess abnormal returns are rarely significantly different from average returns for the entire year. This is partially because seasonalities tend to affect winners and losers to a broadly similar extent.

6.5 Robustness of results

The robustness of the above results is examined in three ways. First, the out-of-sample robustness of the key findings is analysed by examining the pattern of returns in the period 2007-09. Second, an analysis of sub-period returns is conducted in order to assess whether any positive average abnormal returns are largely attributable to the extremely profitable performance of the strategy in a small number of sub-periods. Third, a number of methods are employed to ascertain whether any abnormal returns are driven by the dynamics of a relatively small number of stocks.

6.5.1 Out-of-sample returns

The above results suggest that the contrarian investment strategy is profitable in three of the four countries examined. It is optimum for an investor to focus on extreme stocks and to skip certain portions of holding periods in two of the markets. Significant evidence of momentum is documented for Ireland. These findings are tested in the out-of-sample holding period (2007-09) in order to ascertain the out-of-sample validity of the results[107]. This section also examines the relationship between the returns to the two anomalies and market returns. Table 6.8 and figure 6.7 present the excess abnormal returns to the basic contrarian and momentum strategies in each of the four countries using three- and one-year holding periods respectively[108].

[107] Note that for the contrarian strategy it is assumed that the market model alpha and beta are the same for 2007-09 as they were for the period 1989-2006.
[108] In order to save space, the data in figure 6.7 is the average return in each market over the three models employed.

Table 6.8

Out-of-sample abnormal returns (2007-09)

The table presents the out-of-sample abnormal returns. The contrarian returns are cumulative excess abnormal returns for the three-year holding period (2007-09). The strength rule figures are the average of three holding periods (2007, 2008, and 2009).

Panel A: Contrarian strategy

Model	Ireland	Greece	Norway	Denmark
Adjusted Mkt. Model	-0.432	0.140	0.187	0.203
Market Model	0.219	0.162	-0.036	0.284
CAPM	0.393	0.418	0.145	0.265

Panel B: Strength rule

Model	Ireland	Greece	Norway	Denmark
Adjusted Mkt. Model	0.119****	-0.133*	-0.131*	-0.053
	(2.13)	(-4.47)	(-3.10)	(-0.56)
Market Model	0.308***	-0.040	-0.159***	-0.081
	(2.73)	(-0.80)	(-2.71)	(-0.65)
CAPM	0.086	-0.143	-0.077	-0.035
	(0.95)	(-0.51)	(-1.70)	(-0.41)

* Significant at the 1% level[109]
** Significant at the 5% level
*** Significant at the 10% level
**** Significant at the 20% level

Broadly speaking, the out-of-sample results confirm the earlier findings with the contrarian strategy generating positive abnormal returns in all four countries. As in the main dataset, the largest returns are generated in Greece with the lowest returns in Ireland. The high negative strength rule returns in Greece confirm the earlier findings and add further weight to the conclusion that return reversals are ubiquitous in Greece. Strength rule returns increased dramatically in Ireland and contrarian returns remained robust in the other three markets and were statistically significant in Ireland for two of the three models employed.

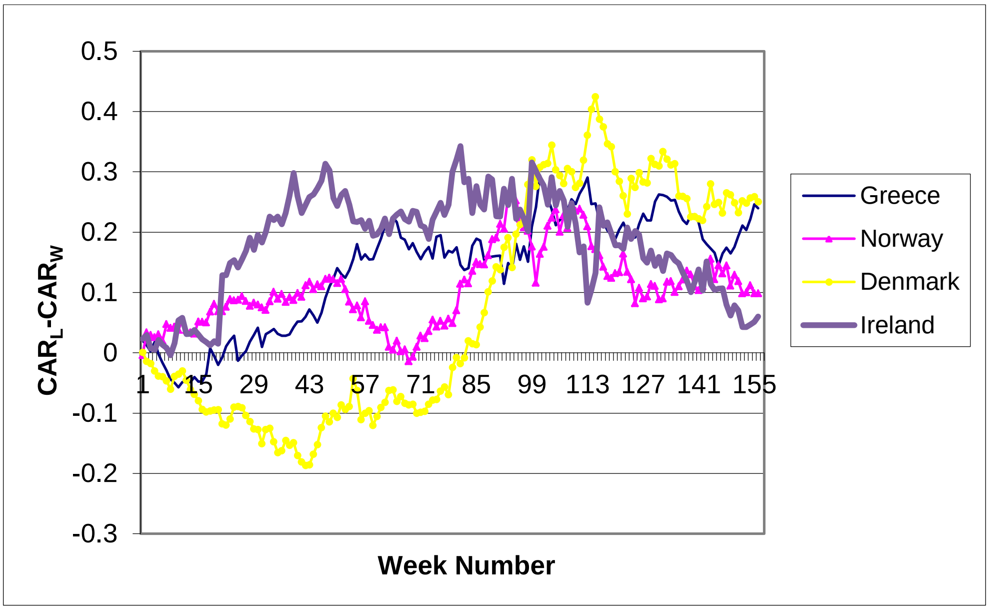
[109] With only one contrarian holding period it is not possible to estimate standard errors using the approach outlined in section 5.4.

Figure 6.7

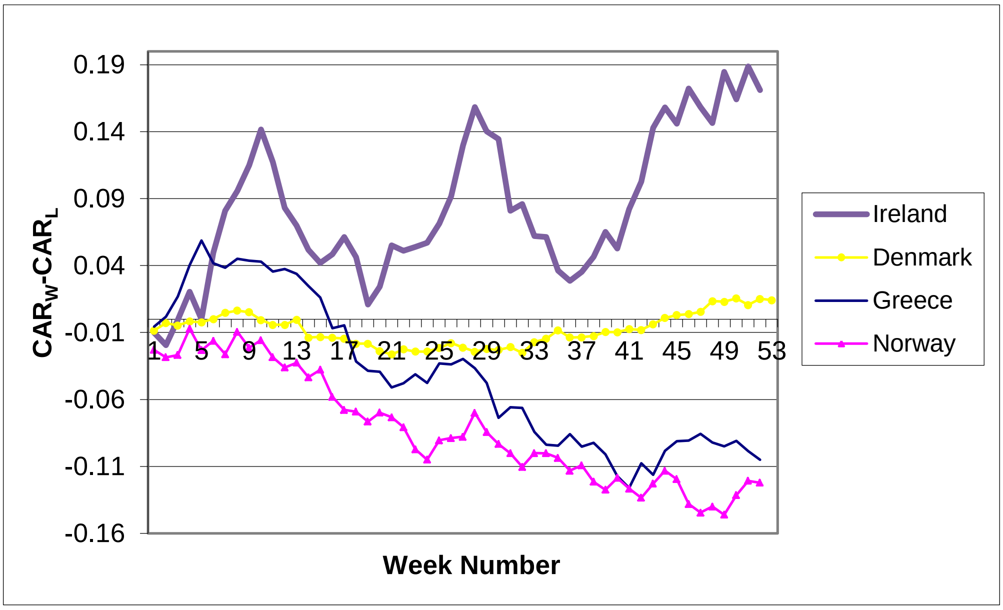
Average out-of-sample returns (2007-09)

Panels A and B chart the average contrarian and strength rule returns, respectively, for the out-of-sample period (2007-09) in the four markets. Each line represents the average of the three models employed.

Panel A: Contrarian investment strategy returns



Panel B: Strength rule returns



Over the out-of-sample period both past winners and losers experienced substantial losses as a result of the global financial crisis. Consistent with the overreaction hypothesis, past winners declined to a greater extent than past losers, resulting in positive returns to the contrarian investment strategy in all four markets. It appears that the ability to short sell is crucial to the contrarian strategy in times of economic downturn. Further analysis of the role of macroeconomic growth rates is presented in section 6.5.2.

The pattern of returns in figure 6.7 validates the earlier findings relating to Greece as abnormal returns are insignificant in the first six months and final year of the three-year test period. When these months are excluded the contrarian strategy generates average excess abnormal returns of 1.6% per month, rising to 1.77% when portfolios are constructed using the two extreme past winners and losers.

The pattern of returns in Denmark is replicated in the out-of-sample period, with significantly negative returns in year one and positive returns thereafter. The contrarian strategy generates average abnormal returns of 1.22% per month in years two and three when applied to all stocks, and 0.7% per month when implemented on extreme portfolios of four winners and losers.

The contrarian strategy generates average abnormal returns of 0.3% per month over the standard three-year holding period in Norway. However, the use of extreme stocks results in negative contrarian returns on average. This is entirely attributable to the large negative abnormal returns in the third holding year.

Perhaps the most cogent conclusion from the preceding analysis is that returns reversals are pervasive in the second year after portfolio formation in all three markets. A relatively straightforward approach of implementing a contrarian investment strategy in year two alone generates average excess abnormal returns of 0.6, 2.8, and 1.2% per month in Greece, Denmark, and Norway, respectively, rising to 1.8, 4.6, and 1.8%, respectively when extreme portfolios are used.

It can thus be seen that the anomalous returns to the contrarian strategy are robust to out-of-sample testing. The remainder of this section focuses on the strength rule strategy. Recall that Ireland was the only market with significant momentum returns. Table 6.9 and figure 6.8 present the excess abnormal returns to various rank and holding periods for the out-of-sample period[110].

Table 6.9

Alternative strength rule returns (2007-09)

The table presents the average monthly excess abnormal strength rule returns for a number of alternative rank and holding periods ranging from three to 12 months. The returns are based on equally-weighted portfolios of market model returns. One-tail t-statistics are reported in parentheses.

	Holding period (months)			
Rank period (months)	**3**	**6**	**9**	**12**
3	4.31***	1.60***	0.16	1.23
	(2.63)	(2.29)	(0.20)	(1.51)
6	3.65***	1.61	1.11	1.91***
	(2.83)	(1.87)	(1.28)	(2.13)
9	4.99**	2.28**	1.32	2.16***
	(3.55)	(2.93)	(1.56)	(2.50)
12	4.37***	2.50**	1.35	2.26***
	(2.87)	(3.39)	(1.70)	(2.73)

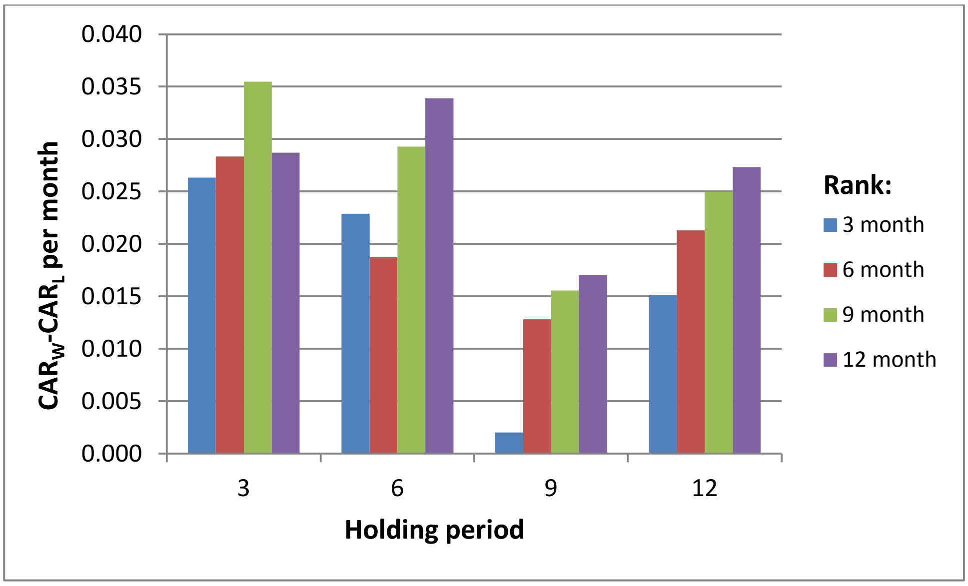
* significant at the 1% level
** significant at the 5% level
*** significant at the 10% level

[110] Recall that the use of extreme stocks did not increase momentum returns in Ireland. Thus, winner and loser portfolios are formed using the top and bottom half of stocks respectively.

Figure 6.8

Excess abnormal returns to strength rule strategies

The figure charts the excess abnormal market model returns to strength rule strategies based on alternative rank and holding periods, as outlined in table 6.9.

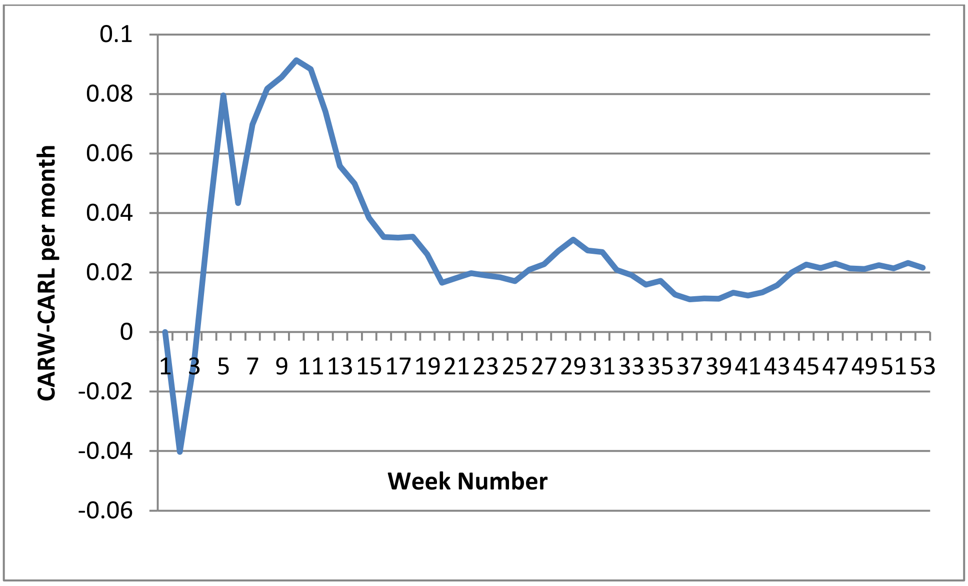


As with the main dataset, returns are generally larger for shorter holding periods and longer rank periods and the 9,3 strategy is optimum in terms of the 16 rank and holding period combinations. Figure 6.9 plots the average monthly market model excess abnormal returns for nine-month ranking periods and holding periods ranging from one week to one year.

Figure 6.9

Average monthly momentum returns (2007-09)

The chart details the average monthly market model abnormal returns to the strength rule strategy in Ireland for the out-of-sample testing period.



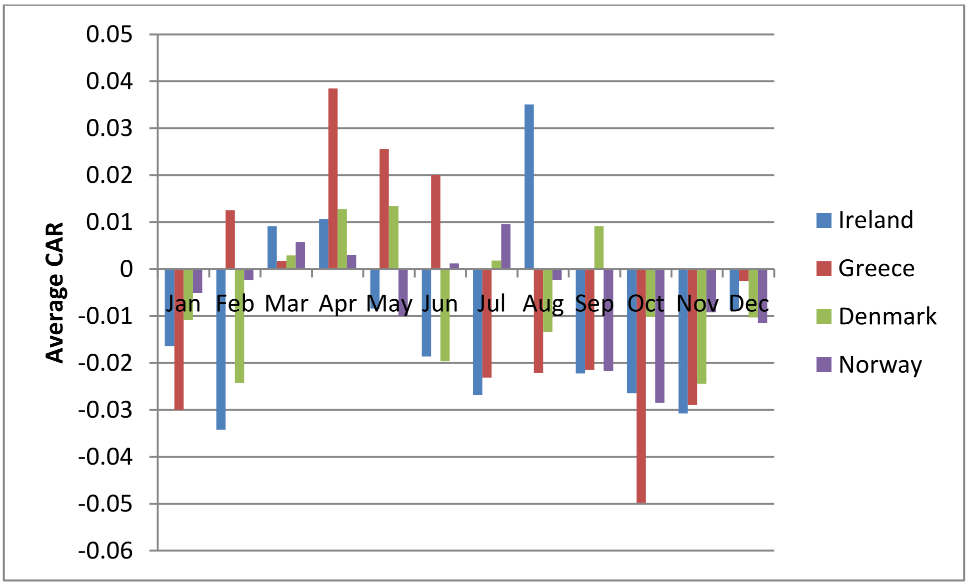
As with the main data period, a relatively short holding period is optimum and the returns to the strength rule are negative in week one. Recall that the optimum strength rule strategy in Ireland involved a nine-month rank and seven-week holding period. The out-of-sample excess abnormal returns to this strategy for the adjusted market model, market model, and CAPM are 8.17, 4.33, and 6.27% per month respectively. The pattern of returns is very similar to that presented in figure 6.4, suggesting that the conclusions reached in section 6.2.1 are robust.

The final test in this section examines the out-of-sample abnormal returns for each month in order to assess the robustness of the seasonal effects discussed in section 6.4. Such returns are detailed in figure 6.10.

Figure 6.10

Average monthly abnormal returns (2006-09)

The chart shows the average monthly returns for all stocks over the period 2006-09 and is the out-of-sample equivalent of figure 6.2. The data is calculated by taking the average of the returns to all stocks. The data is derived from the strength rule holding periods. The results are almost identical when the contrarian periods are used.



The out-of-sample results confirm many of the patterns presented in figure 6.2. For example, the cyclical pattern of returns in Greece is repeated, as are the positive returns in April in all markets. The negative returns in the second half of the year in all markets are partially consistent with the earlier findings, especially those relating to Norway. Indeed, abnormal returns in Norway are negative in all three holding periods in September and October. This adds further robustness to the finding outlined in section 6.4 that returns in these months were negative in 14 of the 17 main sample holding periods.

The negative returns in all four markets from October to December are consistent with the findings of De Bondt and Thaler (1985), who state such a pattern suggests that the high January returns in their sample are most likely attributable to tax-loss selling. However, the negative returns in January for the four markets in this study cast considerable doubt over this hypothesis.

In two respects the results contrast starkly with the findings from the main data period. First, there is a manifest reversal in the pattern of January returns, with negative returns in the first month of the year in all four markets. Second, the positive abnormal returns in Norway have disappeared or reversed.

It is important to note that the returns in the above chart are the average of three year's returns, while the main period data is computed as the average of 17 years. Furthermore, the recession resulted in negative returns in the majority of months. It would be of interest to reassess the robustness of the patterns outlined in section 6.4 in a period of greater economic stability.

6.5.2 Macroeconomic cycle

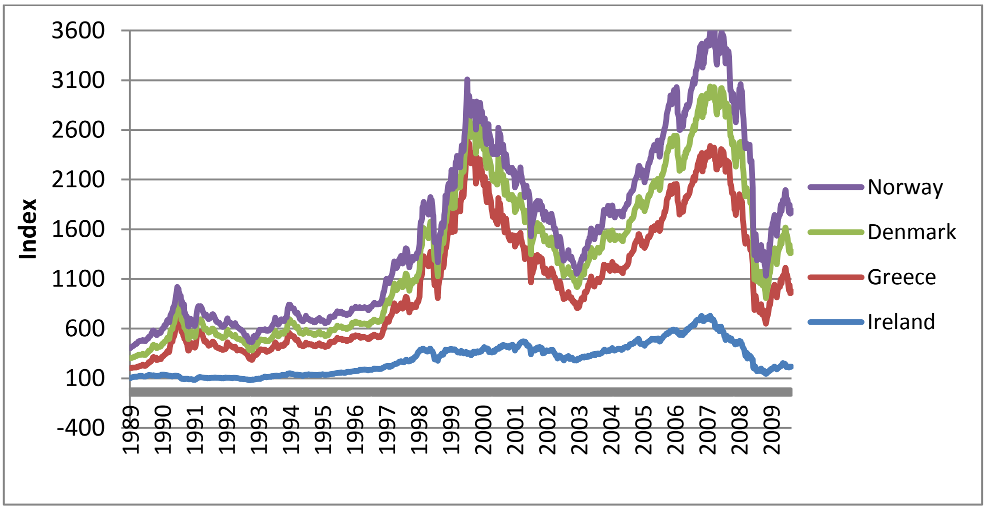
The positive returns to the contrarian strategy in Ireland detailed in the previous section contradict the findings for the main dataset. The out-of-sample period coincided with a time of intense market downturn caused by the global financial crisis and the resultant prolonged recessions in the four markets under review. Over a period of approximately 18 months, starting in mid-to-late 2007, market indices fell from their peaks by 80, 72, 65, and 58% in Ireland, Greece, Norway, and Denmark, respectively.

It is expected that past winners (whose prices may be seen as overvalued) would decline to a greater degree than past losers. Thus, one may expect to find increased (decreased) returns to a contrarian investment (momentum) strategy during such periods. Figure 6.11 charts the market indices over the entire sample period (1989-2009).

Figure 6.11

Aggregate market performance (1989-2009)

The graph charts the trajectory of the market indices for Ireland (ISEQ), Norway (OBX), Denmark (OMX20), and Greece (ASE) for the data period 1989-2009. All indices are rebased to 100 on January 1st 1989.



The pattern of return continuation followed by sharp reversals is manifest in the graph at the market level. The vicissitudes in market returns are consistent with the phenomenon of mean reversion, which Poterba and Summers (1988) link to noise traders. The reversal pattern appears to be particularly pronounced. While serial correlation coefficients are close to zero for one-year lagged market returns, they range from -0.34 in Greece to -0.62 in Norway for three-year returns.

The elevated returns to the two anomalies during market contractions generalises to the entire sample period. On average, the contrarian (strength rule) strategy generates abnormal returns of 23.5% (7%) in the four markets when the market index declines, compared to an average of 10.1% (-5.3%) in up markets. These averages in bear markets are not the result of a small number of unrepresentative periods. Abnormal returns to the contrarian and strength rule strategies are positive in 89% and 67% of holding periods, respectively.

Table 6.10 presents further details on the relationship between the abnormal returns to the two trading strategies and market returns. Annual (three-year) market returns are regressed on the returns for the strength rule (contrarian) strategy for each period.

Table 6.10

Relationship between anomalous returns and market returns

The table presents the coefficients in each country arising from regressions of market returns on the contemporaneous abnormal returns to each strategy. Each coefficient is calculated using returns from 20 (six) holding periods for the strength rule (contrarian strategy).

Strategy	Ireland	Greece	Denmark	Norway
Strength Rule	-0.240	-0.099	-0.126	-0.557
R	-0.45	-0.18	-0.15	-0.54
t-statistic	-2.14**	-0.78	-0.66	-2.71**
Contrarian	-0.513	0.286	-0.300	0.105
R	-0.96	0.51	-0.75	0.14
t-statistic	-7.29*	1.19	-2.3**	0.28

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

There is a negative correlation between strength rule returns and market returns in all four markets. However, the relationship is only statistically significant in Ireland and Norway. There is a high negative correlation between contrarian and market returns in Ireland and Denmark, with a strong positive correlation in Greece and no distinct relationship in Norway. In three of the four markets the results are similar when GNP or GDP is used instead of market returns as there is a high correlation between these variables and market returns. However, in Greece the correlation between market returns and economic growth is virtually zero. The correlation between contrarian returns and GDP growth is -0.65, compared to +0.51 in the case of market index returns.

The results pertaining to Ireland are in stark contrast with those of O'Sullivan and O'Sullivan (2010) and O' Donnell and Baur (2009), who find that momentum strategies in Ireland generate more significant returns in periods of higher market growth. In general, the findings relating to momentum are consistent with studies in international markets, such as, Griffin *et al.* (2003) and Rey and Schmid (2007). However, they contradict the findings of researchers such as Ismail (2012), Du *et al*. (2009), Cooper *et al*. (2004), who show that momentum strategies only generate economically significant results in bull markets.

It is also of interest to examine the relationship between anomalous returns and lagged market returns, following the approach of Cooper *et al*. (2004), as outlined in section 2.5. It is found that contrarian returns are generally higher following bull markets in all countries except Norway. The average correlation between contrarian returns and lagged market returns in these three markets is 0.43 and average returns following bull and bear markets are 15.5% and -16.6%, respectively[111]. These findings directly contrast with those of Hirschey (2003), Ismail (2012) and Chen *et al*. (2012), who find that contrarian returns are larger following down markets in the US, Egypt, and China respectively. The results imply that investors overreact to a greater extent to good news.

In contrast, there is no discernible pattern for momentum returns and lagged market returns in any of the four markets. This suggests that behavioural models such as those developed by Daniel *et al*. (1998) and Barberis *et al*. (2001) cannot fully explain momentum followed by reversal, as such models predict that the returns to both momentum and contrarian strategies will be larger following bull markets due to the increased overconfidence and reduced risk aversion that accompany greater wealth.

In one important respect the results of this study differ from those of Cooper *et al.* (2004) and lend support to the behavioural explanations of the two anomalies. There is a strong positive relationship between contrarian returns and lagged momentum returns in two of the three markets that exhibit significant return reversals (Greece and Denmark). It thus seems that return reversals may be the result of an unwinding of previous momentum, consistent with the overreaction hypothesis.

[111] The dichotomy in the relationships between anomalous returns and contemporaneous and lagged market returns is to be expected given the negative serial correlation in market returns, as outlined earlier in this section.

6.5.3 Sub-period analysis

The out-of-sample returns are derived from a relatively small number of holding periods. Thus, the results from the main data period may be more robust. In addition to analysing the average returns to each strategy, it is instructive to examine number of sub-periods in which each strategy generates positive excess abnormal returns.

This is the second test for the robustness of the results. It is of importance because although a strategy may perform well on average, such a result may be skewed by one sub-period in which the strategy performs extremely well. It could be expected that by pure chance alone, in an efficient market, each strategy would succeed 50% of the time[112]. A significantly higher percentage than this may provide further evidence of a violation of the EMH.

The contrarian strategy generates positive abnormal returns in 89% of holding periods in Greece, with success rates of 67% in Denmark and Norway. The contrarian strategy implemented in the second holding year generates positive returns in 78, 72, and 72% of the holding periods in Greece, Denmark, and Norway, respectively. The strategy generates abnormal returns in less than two-fifths of holding periods in Ireland, providing further evidence of the propensity for return continuation in Ireland.

The 9,3 momentum strategy in Ireland generates positive abnormal returns in approximately 83% of holding periods. The strength rule generates positive returns in Greece in only 28% of holding periods, adding further weight to the findings outlined in section 6.2. The propensity towards reversals is so pronounced that a contrarian strategy generates positive abnormal returns in the majority of one-year holding periods, a time-frame over which continuation is more generally observed. These results show that the anomalous evidence presented in section 6.2 is not attributable to a small number of unusually high and unrepresentative sub-periods.

[112] Recall that for the market to be efficient it is not necessary that no strategy is profitable; merely that one cannot predict *ex ante* which strategy will succeed.

6.5.4 Firm-level dynamics

The final robustness test examines abnormal returns at the firm level. In theory, the contrarian investment strategy could be profitable because one stock switches from being a winner to a loser and *vice versa*. The opposite is true for strength rule returns. This section thus tests whether any positive excess abnormal returns are due to the dynamics of a small number of stocks. This gives an insight into whether one would expect the strategy to be profitable in the future or whether large returns are caused by events unlikely to be repeated. The results that follow relate to the basic strategy in each market.

It may be expected that each stock has a 50% chance of remaining within the winner or loser portfolio over successive ranking periods. Table 6.11 details the percentage of stocks that move from (remain within) portfolios when examining contrarian (strength rule) strategy, with the associated z-score in parentheses for the one-tailed test that the average proportion is significantly greater than the hypothesised value of 50%.

Table 6.11

Movement of shares between winner and loser portfolios

The table reports the percentage of shares switching (remaining within) portfolios for the contrarian strategy (strength rule). The figures are the average of five (17) holding periods with z-scores in parentheses.

Contrarian	**Ireland**	**Greece**	**Norway**	**Denmark**
Percentage moving	49.2	64.9*	54.8**	49.8
	(-0.22)	(5.34)	(1.85)	(-0.06)
Strength rule	**Ireland**	**Greece**	**Norway**	**Denmark**
Percentage staying	53.9*	44.6*	50.2	50.5
	(2.63)	(-2.94)	(0.11)	(0.24)

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

The results show that the significant contrarian returns in Greece are not driven by the dynamics of a small number of stocks. Instead, there is a marked tendency for stocks to switch portfolio, even with the strength rule and its one-year rank periods. There is also evidence of a tendency for stocks to switch portfolios in Norway over three-year holding periods and evidence of return persistence in Ireland. In all other cases, the proportion of stocks moving or staying is not statistically different from the hypothesised value of 50%.

The robustness of the above results can be further examined using a non-parametric technique based on 2x2 contingency tables and the cross-product (or log-odds) ratio, as employed by Brown and Goetzmann (1995) in measuring persistence in mutual fund performance[113].

Stocks are ranked as winners (W) or losers (L) in consecutive periods, giving four possible combinations over each pair of periods. Continuation exists when a stock is a winner or loser in consecutive periods (WW and LL respectively), while reversal occurs when a stock alternates between being a winner and loser (WL and LW). The number of stocks falling into each category is recorded and the cross-product ratio calculated as:

$$\text{Cross-product ratio} = \frac{WW*LL}{WL*LW} \qquad (6.1)$$

The inverse of the above equation is used when testing the contrarian investment strategy and the propensity of stocks to move from one portfolio to another. In both cases, under the null hypothesis of no serial correlation in returns the cross-product ratio will equal one. A ratio significantly greater than one rejects the null hypothesis, thereby suggesting significant structure (serial correlation) in the ranking of returns.

The statistical significance is estimated by scaling the log of the cross-product ratio by its standard error, which is estimated as:

$$\sqrt{\left(\frac{1}{WW}\right)+\left(\frac{1}{WL}\right)+\left(\frac{1}{LW}\right)+\left(\frac{1}{LL}\right)} \qquad (6.2)$$

[113] Building on the work of Brown *et al.* (1992) and Goetzmann and Ibbotson (1994).

Table 6.12

Contingency table and cross-product ratios

The table details the number of stocks classified as winners or losers in consecutive periods. The number of instances in each category is calculated as the average of three models, which in turn are the average of six (20) pairs of ranking periods for the contrarian (strength rule) strategy.

Contrarian	**WW**	**LL**	**WL**	**LW**	**Cross-product ratio**	**z-score**
Ireland	36.33	36	36	35.67	0.981	-0.05
Greece	20.33	20.67	35.33	35.67	3.00	2.80*
Norway	31	30.67	35.67	36	1.350	0.86
Denmark	31	31	31	31	1	0
Strength Rule						
Ireland	133.67	137.33	119.33	115.67	1.330	1.60***
Greece	93.67	93.67	114.33	114.33	0.671	-2.02**
Norway	122	122	121.67	121.67	1.005	0.03
Denmark	110	110	107	107	1.057	0.28

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

It is once again clear to see that there is a strong tendency towards reversals in Greece. This reversal of performance is so pronounced that even in the case of the strength rule, stocks have a strong propensity to switch portfolios over one-year rank periods. There is a clear propensity towards continuation in Ireland. There is no statistically significant pattern in the other markets on average.

The above analysis is merely dependent on whether or not a stock remains within the same portfolio. A more thorough insight into the dynamics of individual stocks can be obtained by examining Spearman's Rank Correlation Coefficient, as this will also indicate movement within each portfolio. If there is significant momentum (reversal) in returns then one would expect a high positive (negative) correlation coefficient, while a coefficient close to zero would suggest a lack of structure in returns.

Table 6.13 details the average rank correlation coefficient for each country and model. The average for each model is derived from six (20) pairs of rank periods for the contrarian (momentum) strategy. As correlation coefficients are not additive, it is necessary to transform the coefficients into Fisher Z values using equation (6.3).

$$Z = \frac{1}{2}\ln\left[\frac{(1+r)}{(1-r)}\right] \qquad (6.3)$$

These Z values are then averaged and the Fisher Weighted Mean Correlation Coefficient, $\bar{r}$, is computed as:

$$\bar{r} = \frac{e^{\bar{z}} - e^{-\bar{z}}}{e^{\bar{z}} + e^{-\bar{z}}} \qquad (6.4)$$

The statistical significance of $\bar{r}$ can be estimated using:

$$t = \bar{r}\sqrt{\frac{n-2}{1-r^2}} \qquad (6.5)$$

Table 6.13

Average rank correlation coefficient

The table details the average rank correlation coefficient for both strategies with t-statistics in parentheses. The figure for each model and country represents the mean coefficient of six (20) pairs of rank periods for the contrarian (momentum) strategy after converting coefficients to Fisher Z values.

	Ireland	**Greece**	**Norway**	**Denmark**
Contrarian	0.095	-0.385**	-0.181	-0.064
	(0.47)	(-2.05)	(-0.91)	(-0.32)
Strength Rule	0.121	-0.146	0.043	0.052
	(0.59)	(-0.73)	(0.21)	(0.25)

** significant at the 5% level

The large and significant negative coefficient in Greece violates the null hypothesis that consecutive rankings are independent of each other. In Greece the rank correlation coefficient was of the expected sign in 17 of the 18 contrarian paired rank periods and was also negative in 35 of the 60 paired rank periods for the momentum strategy. There is no distinct and significant pattern in the other markets.

Taken together, the results in this section provide a clearer picture of the robustness of return reversals. For each of the three measures, the evidence is consistent with the ranking of reversals outlined in the preceding sections. The most robust evidence relates to Greece, where there is a marked tendency for stocks to move from one portfolio to another. The strength rule returns in Ireland are also robust. The evidence in Norway is less robust, while the results suggest that the contrarian returns in Denmark are driven by extreme reversals of a relatively small group of stocks.

Further analysis shows that the firms that comprise the winner and loser portfolios do not systematically and significantly differ on key firm-specific characteristics such as firm size, share price, and beta. This suggests that the anomalous returns in this chapter are not driven by risk, or microstructure biases, such as bid-ask spread and illiquidity.

6.6 Conclusion

This chapter examines the returns to contrarian investment and strength rule strategies in four medium-sized European markets using three models with varying degrees of sophistication in their treatment of risk. Significant and robust evidence of structure in returns is presented in violation of the null hypothesis of market efficiency.

The contrarian strategy generates positive excess abnormal returns in three of the four markets. The most economically and statistically significant returns are in Greece, where return reversals result in average excess abnormal contrarian returns of 40.7% over a three-year holding period. It is shown that excess abnormal returns can be enriched via the use of various holding periods and by focusing on extreme stocks. In general, average monthly abnormal returns increase with longer rank and holding periods. The high returns to the strategy using six-month rank periods in Greece and Norway are notable exceptions and contradict the characteristic finding of medium-term continuation in the literature.

Perhaps the most robust and lucid finding is the tendency towards return reversals in the second year following portfolio formation. A contrarian investment strategy implemented in year two alone generates consistent and economically significant excess abnormal returns, as it profits from stylised finding of momentum followed by reversal. The returns to such a strategy are particularly striking when portfolios are constructed with extreme stocks.

Ireland is the only country where significant strength rule returns are consistently observed. The optimum strategy involves ranking stocks over nine months and implementing the momentum strategy for approximately two months. The superiority of a relatively short holding period is consistent with the findings of key momentum studies such as Jegadeesh and Titman (1993) and Rouwenhorst (1998). However, the nine-month rank period contrasts with the 12-month period that is found to be optimal in such studies. The negative returns to the portfolio of past losers suggest that return continuation in Ireland is not confined to past winners.

The role of risk does not appear to be as important as stated in previous research, such as Chan (1988). Although in some cases the use of the CAPM reduces abnormal returns it does not do so to such an extent that it can be cited as a major explanatory variable in the large returns. Furthermore, the abnormal returns cannot be explained by microstructure biases, macroceconomic risk, and short-selling constraints. Moreover, the anomalous evidence is robust to out-of-sample testing, is not attributable to the dynamics of a small number of stocks, and is not limited to a small number of holding periods with disproportionately large abnormal returns.

A number of noteworthy seasonal patterns emerged in this chapter. Abnormal returns are positive in January, April and May and negative in September in all four markets. However, in all markets excess abnormal returns remain significant when such months are omitted.

Therefore, one can conclude that the anomalous returns presented in this chapter are more than mere manifestations of seasonal anomalies. Both strategies generate particularly elevated abnormal returns during economic downturns and contrarian returns tend to be more significant following market upturns. The latter finding presents a potentially useful *ex ante* trading strategy.

It is noteworthy that the most significant anomalous returns are observed in Greece and Ireland. These are the two smaller markets in the sample and they suffered to the greatest extent in the stock market crashes at the time of the global financial crisis. This finding may support the assertion of Dreman and Lufkin (2000, p.61) that overreaction "can be the major cause of financial bubbles and panics". The finding may also point towards an important role for noise traders, as Palomino (1996) shows that such traders are more likely to survive in small markets. As there was no dominant industry in Ireland or Greece (see section 5.2.1), it appears that the anomalous returns are not attributable to industry momentum or reversal, or cross-sectional dependence in firm's returns.

In summary, the evidence in this chapter provides out-of-sample confirmation of the validity of return continuation and reversal and casts further doubt on standard finance theory's assumption of market efficiency. Rational explanations are incapable of fully accounting for the significant abnormal returns presented in this chapter. The next chapter examines whether brokers play an important role in explaining this anomalous evidence.

Chapter Seven

Broker Findings and Discussion

7.1 Introduction

This chapter discusses the findings of tests relating to brokers' output. Three principal forms of such output are analysed; price forecasts, EPS forecasts, and the overall recommendation category. It is important at the outset to a make a clear distinction between the terms used to describe these three forms of prognostication made by brokers. The term 'forecast' specifically refers to EPS forecasts, while 'target' is used for brokers' price target and 'recommendation' is used to describe the overall recommendation category. Existing research tends to focus on one of the above three variables. This thesis examines the interaction between the variables in order to obtain a more complete picture of the value, veracity, and impact of brokers' output. There is also a sharp focus on the relationship between brokers' output and return momentum.

The output of brokers is examined along three temporal dimensions. First, contemporaneous targets and recommendations are analysed in order to ascertain whether brokers' advice is consistent with their predictions. Measures of herding and optimism are also examined. Second, brokers' output is compared to past variables, such as momentum, size, and book-to-market value, in order to provide an insight into whether brokers follow momentum or value strategies. Finally, the value and impact of brokers' output is examined by comparing targets and recommendations with future abnormal returns and volume. The absolute level of brokers' output is analysed, along with revisions to target prices and recommendation levels. Furthermore, a comparison is drawn between Irish and non-Irish brokerage firms, as it is hypothesised that the former are more prone to conflicts of interest.

The remainder of this chapter is structured as follows. Section 7.2 examines recommendation levels; price and EPS forecasts are analysed in sections 7.3 and 7.4, respectively. Section 7.5 examines the firm-specific characteristics of stocks that analysts recommend favourably. The price and volume impacts of brokers' output are discussed in section 7.6 and section 7.7 draws conclusions.

7.2 Findings

This section presents the findings relating to the nature of recommendations. The number of recommendations falling into each of the five categories is analysed and measures that capture the level of analyst optimism and herding are presented. The responsiveness of analysts in terms of recommendation revisions is also examined and any differences between Irish brokers and their international counterparts are highlighted.

7.2.1 Recommendation categories

Table 7.1 and figure 7.1 present statistics on the frequency of recommendations by category. Each of the 70,794 recommendations is assigned to one of the five categories using the coding system outlined in table 5.5. It is clear that there is a significant positive bias in recommendations and Irish brokers are considerably more optimistic in their outlook than non-Irish brokers.

The overall level of optimism is significantly higher for brokers covering Irish stocks than in the existing literature covering a variety of markets. However, the most striking aspect of table 7.1 is the stark contrast between Irish brokers and their international counterparts. As predicted by the conflicts of interest literature, the home-based analysts exhibit a higher level of optimism. Remarkably, one Irish broker issued 8,088 recommendations with only 83 'reduce' and zero 'sell' recommendations.

Table 7.1

Percentage of recommendations by category

Panel A reports the percentage of recommendations falling into each of the five categories (N = 70,794). Panel B reports the ratio of positive (buy and add) to negative (reduce and sell) recommendations and the ratio of buy-to-sell recommendations.

Panel A: Recommendations by category

Category	All	%	Irish	%	Non-Irish	%
Buy	27,321	38.58	11,724	55.70	15,597	31.35
Add	16,868	23.83	5,271	25.04	11,597	23.31
Hold	21,050	29.74	3,348	15.91	17,702	35.58
Reduce	3,597	5.08	652	3.10	2945	5.92
Sell	1,958	2.77	53	0.25	1905	3.83
Total	**70,794**	**100**	**21,048**	**100**	**49,746**	**100**

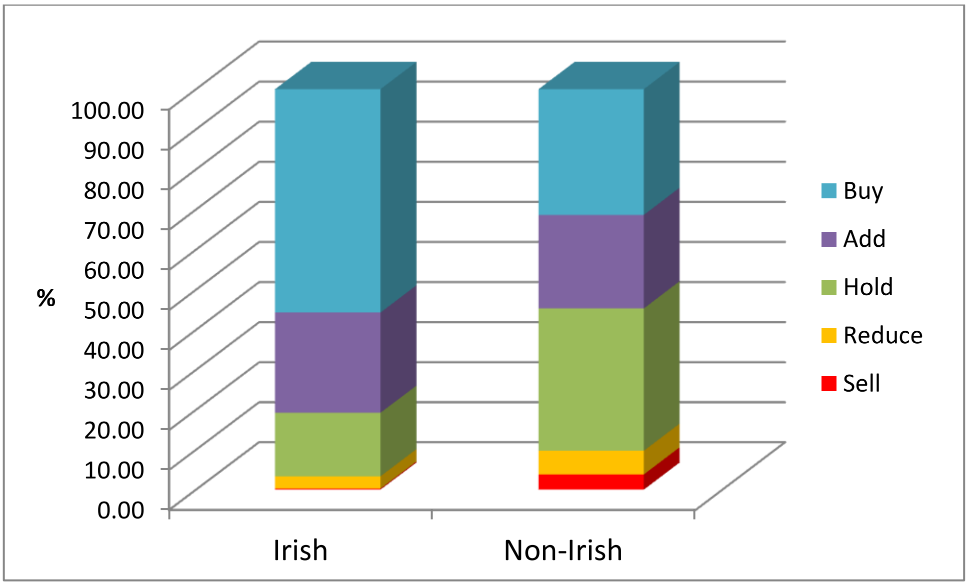
Panel B: Recommendation ratios

Broker	Positive-to-negative	Buy-to-Sell
All	7.95	13.95
Irish	24.10	221.21
Others	5.61	8.19

Figure 7.1

Percentage of recommendations by category

The chart shows the breakdown of recommendations by category using the coding system outlined in table 5.5.



To the best of the author's knowledge, the buy-to-sell ratio of approximately 221:1 dwarves any equivalent ratio in the literature. The ratio of positive-to-negative ratios is equally elevated by international standards. The level of optimism is also in stark contrast with the findings of Ryan (2006) who documents an average ratio of 7.2:1 for three Irish and one non-Irish broker. Appendix F provides a basis for an international comparison.

Following Ryan (2006), the above ratios are re-calculated by excluding instances where multiple brokers issue the same contemporaneous recommendation. In the dataset of 70,794 recommendations, there are 28,069 unique recommendations. Table 7.2 details the number of unique recommendations by category[114]. The resulting buy-to-sell ratio is 6.9:1, marginally higher the equivalent figure of 5.9:1 reported by Ryan (2006). The ratio of positive-to-negative recommendations decreases to 4.4:1 when common recommendations are excluded.

Table 7.2

Details of unique recommendations

The table reports the number of unique recommendations made by category. Contemporaneous recommendations of the same type are excluded for each set of brokers.

Category	All	%	Irish	%	Non-Irish	%
Buy	9,300	33.2	7,249	47.5	6,161	30.2
Add	7,483	26.7	4,382	28.7	4,731	23.2
Hold	7,479	26.6	2,968	19.5	6,156	30.2
Reduce	2,453	8.7	603	4.0	2,045	10.0
Sell	1,354	4.8	53	0.3	1,301	6.4
Total	**28,069**	**100**	**15,255**	**100**	**20,394**	**100**

However, the ratios for the Irish brokers remain considerably elevated at close to 137:1, with almost 18 times as many positive as negative recommendations. This occurs despite the finding that there was no instance of two Irish brokers issuing sell recommendations

[114] For the Irish and non-Irish brokers, identical contemporaneous recommendations are only excluded in they are issued by an Irish and non-Irish broker, respectively. Hence, the total number of recommendations in the Irish and non-Irish categories exceeds the number for all brokers, which excludes all common recommendations.

contemporaneously. Thus, the number of unique sell recommendations equals the total number of sell recommendations. The equivalent ratios for international brokers decrease to 4.7 and 3.3 respectively.

Another aspect of the advice given by brokers is their reluctance to use the word 'sell'. In the sample used in this study 26 out of 77 (34%) brokers do not explicitly use the word 'sell' for their lowest recommendation category. Instead phrases such as 'underperform', 'reduce' and 'underweight' are attached to the most negative ratings. This is similar to the 30% reported by Ho and Harris (1998). The above figure is biased downwards, as 30 of the brokers (40%) did not issue any negative recommendations. It is thus not possible to ascertain the exact terminology that such brokers use to communicate their most negative rating.

7.2.2 Optimism index

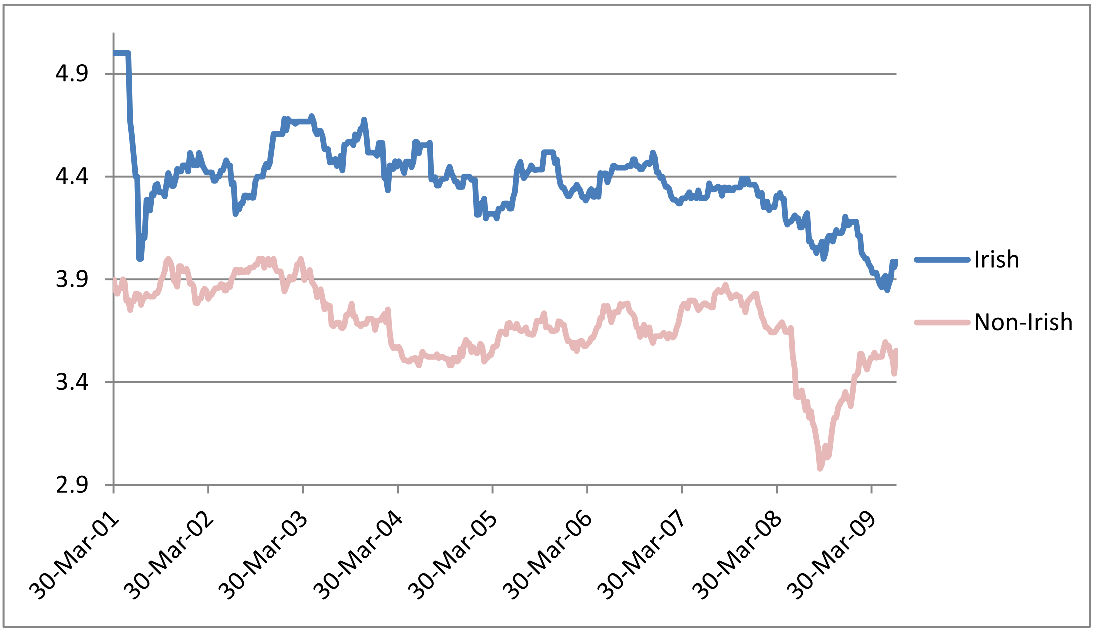
The statistics on the number of recommendations in each category can be used to calculate an optimism index for Irish and non-Irish brokers. The index is calculated as the average value of all recommendations for each set of brokers. Recommendations are coded from sell =1 to buy =5 as detailed in table 5.5. The overall average optimism index is 3.90 for all brokers and 4.32 (3.73) for Irish (non-Irish) brokers. The t-statistic for the difference in means of Irish and non-Irish brokers is 3.67, suggesting that Irish brokers are considerably more optimistic than their international counterparts.

It appears that regulations in Europe have not resulted in a marked decrease in optimism bias. This contrasts with the evidence relating to the US. For example, Barber *et al*. (2006) report a significant decline in the percentage of buy recommendations after the introduction of NASD rule 2711. The figures reported here for non-Irish brokers are in line with those reported in Jegadeesh *et al*. (2004) for the U.S, where the mean consensus level ranges from 3.21 to 3.97 and averages 3.67. Figure 7.2 plots the weekly optimism index for Irish and non-Irish brokers.

Figure 7.2

Average rating (Irish vs. non-Irish brokers)

The figure presents the time series of the average rating for recommendations of Irish and non-Irish brokers. Each week the recommendation of each broker for each company is converted into a rating from one to five and averaged across all firms and brokers. This process is completed for the recommendations of Irish and non-Irish brokers.



Another striking feature of the graph is the relative reluctance of Irish brokers to revise their recommendations downwards to negative ratings. In the period surrounding the global financial crisis, the average recommendation rating for Irish brokers decreased to a smaller extent and in a more delayed fashion than was the case for international brokers. The average rating for international brokers decreased from approximately 3.7 to 3 between April and September 2008. For Irish brokers, the average rating fell from approximately 4.2 to 3.9 and this decrease commenced almost eight months after that of international brokers. The rating of 3.9 shows that, at their most pessimistic, Irish brokers were issuing an ‘add’ recommendation, on average.

7.2.3 Recommendation revisions

The previous sub-section tentatively suggests that Irish analysts are slow to revise their recommendations downwards. Table 7.3 outlines the number of revisions based on the original and new recommendation category. In total, there were 582 downgrades (53%) and 512 upgrades (47%)[115]. Approximately 1.5% of recommendations are revisions, suggesting that analysts covering Irish stocks are considerably more reluctant to revise their recommendations than those covering stocks in the US. For example, Elton *et al.* (1986) report 3,433 revisions in 30,391 recommendations, yielding a revision rate of approximately 11.3%. With five recommendation categories there are 20 possible revision combinations. Any revisions to the left (right) of the main diagonal are upgrades (downgrades).

Table 7.3

Recommendation revisions

The table outlines the number of revisions based on the original and new recommendation category.

		New						
		Buy	**Add**	**Hold**	**Reduce**	**Sell**	**Total**	**%**
Original	**Buy**		160	185	10	7	362	33
	Add	161		103	21	2	287	26
	Hold	160	82		45	40	327	30
	Reduce	9	19	31		9	68	6
	Sell	6	1	38	5		50	5
	Total	336	262	357	81	58	1,096	-
	%	31	24	33	7	5	-	100

The above table reiterates the clear reluctance of analysts to revise recommendations downwards to the two negative ratings. The majority of revisions (55%) are of one degree, with 42% of revisions moving by two degrees and 2% and 1% moving by three and four degrees, respectively. These percentages are the same for upgrades and downgrades. The proportion of multi-level changes is considerably higher than the 10 and 30% reported in Ho and Harris (1998) and Stickel (1995), respectively. The significantly larger proportion of

115 See appendix G for comparable statistics from other studies.

downgrades from hold to sell compared to reduce to sell may be consistent with prospect theory. If a broker risks antagonising a covered company by downgrading their stock to a negative rating, then prospect theory (hedonic framing) suggests that such bad news should be released in one step rather than drip fed to the market.

The reluctance to revise recommendations manifests itself in extended runs of consecutive recommendations of the same category. Table 7.4 presents statistics on the number of weeks over which recommendations remained unchanged.

Table 7.4

Recommendation runs

The table contains summary statistics on the number of consecutive weeks during which recommendation levels remained unchanged, i.e. the length of recommendation runs. All measures are in weeks except for 'runs', which details the number of runs for each category.

	Sell	**Reduce**	**Hold**	**Add**	**Buy**	**Overall**
Runs	76	110	531	435	591	1743
Maximum	156	158	262	297	305	305
Mean	25.9	33.2	24.8	38.7	46.2	40.6
Median	18	25	26	25	30	27
SD	27.8	32.0	39.8	40.9	48.8	42.8

It can be seen that recommendation levels are sticky, and this inertia tends to increase as recommendation levels become more positive, where the maximum unbroken sequence is almost six years[116]. The overall mean run of 40.6 weeks connotes a conspicuous reluctance to revise forecasts on the part of brokers. It presages that analysts do not believe that news is quickly impounded into prices, unless there is a remarkable run of positive serial correlation in news. The long sequence of unchanged recommendations may imply that analysts follow momentum strategies. This will be examined in greater detail in section 7.5. Table 7.5 presents the mean (median) number of weeks over which recommendations remained unchanged following revisions of different types.

[116] The minimum run is one week for all recommendation categories.

Table 7.5

Average sequences following upgrades and downgrades

The table presents the mean (median) number of weeks of consecutive recommendations of the same type following upgrades and downgrades of various degrees.

		New				
		Buy	**Add**	**Hold**	**Reduce**	**Sell**
	Buy		34.4 (19)	38.8 (23)	18.8 (19.5)	18.1 (20)
	Add	44.4 (25)		42.3 (29)	47 (26)	8.5 (8.5)
Original	**Hold**	37.9 (25)	41.6 (29.5)		28.4 (21)	21.6 (16.5)
	Reduce	18.2 (20)	29.2 (25)	34 (24)		17 (8)
	Sell	26.8 (26)	3 (3)	23.3 (17.5)	25.6 (24)	

The table shows that revisions to negative categories are generally left unchanged for a shorter period of time. In general, Irish brokers are more responsive than international brokers. This result is entirely driven by their tendency to leave negative ratings unchanged for shorter periods of time. On average, recommendations remain unchanged for 38 weeks following upgrades and 36 weeks subsequent to downgrades. The difference is larger for Irish brokers (37 versus 30 weeks) than non-Irish brokers (39 versus 38 weeks).

In summary, it appears that Irish brokers are considerably more optimistic than their international counterparts. They are more reluctant to downgrade recommendations to negative ratings and leave such recommendations unchanged for a relatively short time. These findings represent more concrete evidence than Ryan's (2006) interpretation of the significant negative pre-revision abnormal returns to sell recommendations as evidence of Irish analysts' reluctance to downgrade recommendations, possibly due to conflicts of interest.

7.3 Target price

The target price issued by brokers is the second form of output analysed. This variable is examined in three ways. First, the accuracy of the forecasts is analysed by calculating forecast errors. Second, the dispersion of forecasts is examined in order to measure analyst herding. Finally, target prices are compared to recommendation levels in order to ascertain whether brokers' messages are consistent in terms of these two measures of their opinions of a firm's prospects.

The elevated optimism of Irish brokers is evidenced again. On average, the target price issued by Irish brokers is 12.5% higher than the forecast of international brokers. The average target price for Irish brokers exceeds the international average for 17 of the 22 companies for which both sets of brokers issue forecasts.

7.3.1 Forecast accuracy

Following the customary approach of existing studies of brokers' output, the accuracy of price forecasts is analysed by calculating the forecast error of each analyst *i*, for firm *j*, at time *t* (FE_{ijt}) as:

$$FE_{ijt} = \frac{F_{ijt} - P_{jt+1}}{P_{jt+1}} * 100 \qquad (7.1)$$

where: F_{ijt} is the forecast of analyst *i*, for firm *j*, at time *t*.

P_{jt+1} is the actual price of firm *j*, one year later.

On average, consensus forecasts are almost 89% higher than the resulting price, implying strikingly unjustified optimism on the part of brokers. Irish brokers are more optimistic than international analysts with the average price one year after forecasts being 95% lower than the forecasted price. These figures are considerably higher than the equivalent figure of 28% reported in Brav and Lehavy (2003). An analysis of price forecasts also shows that Irish brokers have a greater tendency to herd than their international counterparts. The average coefficient of variation for Irish and non-Irish brokers are 0.115 and 0.158, respectively (t-stat for differences in means = 4.06).

The high level of herding by Irish brokers may explain the optimistic nature of their forecasts and the significant momentum returns in Ireland, as outlined in section 6.2. Olsen (1996) shows that herding leads to an increase in the mean forecast, as analysts tend to herd their optimistic forecasts more often. Furthermore, Du and McEnroe (2011) show that investors are more confident when they receive multiple earnings forecasts with no variability and Welch (2000) shows that herding leads to momentum.

7.3.2 Recommendation level vs. target price

This section examines whether analysts' recommendations and target prices present a consistent picture of their opinions of the prospects of a firm. Kerl and Walter (2008) discuss the recent change in the recommendation categories used by brokers. Banks generally tended to use a five-category scheme for their recommendations, i.e., strong buy, buy, hold, sell, and strong sell. However, in 2002, Lehman Brothers, Morgan Stanley and Goldman Sachs changed to a three-category rating; (overweight, equal-weight, underweight) and most investment banks followed suit (Bradley *et al.*, 2003).

Having a limited number of discrete recommendation categories reduces the degrees of freedom. Naturally, the strength of recommendations relating to stocks that fall into the same category may differ significantly before the point at which one crosses the boundary into the next recommendation category. This limitation is accentuated by the fact that the negative recommendation categories are rarely used, as outlined in section 7.2.1.

In order to overcome this, an index is calculated measuring the expected change in share price implied by a price forecast. This continuous data allows more scope for analysing cross-sectional variation in the strength of the recommendation and its impact on share prices. The anticipated percentage change in share price is calculated as the difference between the forecasted and current share price divided by the current price and multiplied by 100.

$$E\Delta_{ijt} = \frac{\mathrm{F_{ijt+1}} - \mathrm{P_{jt}}}{\mathrm{P_{jt}}} * 100 \qquad (7.2)$$

where: $E\Delta_{ijt}$ is the anticipated change in price forecast by analyst *i*, for firm *j*, at time *t*.

F_{ijt+1} is the forecast of analyst *i*, for firm *j*, for the next period.

P_{jt} is the current price of firm *j*.

The precise meaning of each category in terms of the associated expected change in price varies by broker. This study adopts the most common approach of brokers in this dataset, as detailed in table 7.6.

Table 7.6

Consensus recommendation levels and price targets

The table presents the average expected price change calculated by comparing brokers' target prices with the current price of each firm. The expected changes are allocated to bands and compared to the overall recommendation categories.

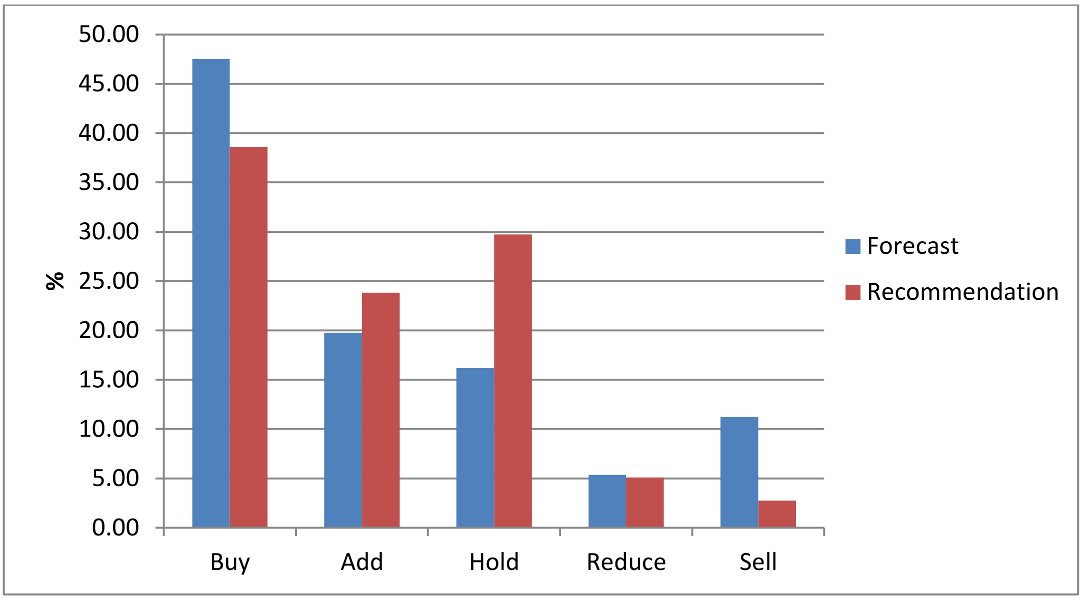
Expected price change	**#**	**%**	**Recommendation category**	**#**	**%**
15%+	3,739	47.52	Buy	27,321	38.59
5 to 15%	1,553	19.74	Add	16,868	23.83
-5 to 5%	1,273	16.18	Hold	21,050	29.73
-5 to -15%	420	5.34	Reduce	3,597	5.08
-15% +	883	11.22	Sell	1,958	2.77
Total	**7,868**	**100**	**Total**	**70,794**	**100**

The general pattern is that price forecasts tend to fall into the extreme ratings more often than recommendation levels. In terms of negative forecasts, one may suspect that forecasted prices are more reflective of the broker's view on the firm's prospects. Perhaps brokers are more willing to issue a forecast that implies selling a stock than they are to issue a report explicitly containing the word 'sell'. Figure 7.3 presents a graphical comparison of price forecasts and recommendation categories.

Figure 7.3

Expected price change vs. recommendation category

The chart compares the percentage of price forecasts (expected price change) and recommendations by category.



The above expected price changes are based on consensus forecasts. Table 7.7 performs a similar analysis using individual price forecasts. This is necessary in order to isolate cases where a forecast and a recommendation were made by the same broker for the same company. There are 45,918 price forecasts, with 41,688 of these having a corresponding recommendation from the same brokerage firm for the firm company in question. If brokers' recommendations are consistent with their forecasts then we would expect to see a pronounced clustering along the diagonal of the matrix[117].

[117] It should be noted that the comparison here is between recommendations by the same brokerage house. However, it is reasonable to assume that in most cases the same broker is responsible for both outputs as individual brokers tend to follow certain companies.

Table 7.7

Comparison of common price forecasts and recommendation categories

The data in the table describes all cases where a brokerage house issued a contemporaneous price forecast and recommendation category. Rankings of 1-5 are assigned to recommendations ranging from sell = 1 to buy = 5. Expected price changes are calculated as the percentage difference between each broker's target price and the current price for each stock. Rankings of 1-5 are then assigned for forecasted changes in the ranges of less than -15%, -15 to -5%, -5 to 5%, 5 to 15%, and greater than 15%, respectively. The sample consists of 41,688 price forecasts and corresponding recommendations and is derived from 61 brokers covering 26 companies. Panel A details the percentage of observations falling into each of the five ratings categories, while summary statistics are detailed in panel B. Panel C presents the correlation coefficients between price forecasts, recommendation categories, and expected price change.

Panel A

N = 41,688		**Recommendation category**				
		1	**2**	**3**	**4**	**5**
Price forecast	**1**	**15.08%**	15.98%	30.20%	12.49%	26.26%
	2	10.74%	**19.06%**	45.89%	12.47%	11.84%
	3	3.11%	9.00%	**41.72%**	23.52%	22.65%
	4	0.96%	2.94%	28.52%	**28.62%**	38.96%
	5	1.32%	4.65%	25.47%	22.27%	**46.29%**

Panel B

	Recommendation Category				
Expected price change	**1**	**2**	**3**	**4**	**5**
#Ob.	1445	2926	12520	9133	15664
Mean	12.64	17.99	40.61	30.22	46.33
Median	-11.28	0.39	11.11	16.98	24.48
Min	-78.97	-69.16	-78.97	-82.39	-80.61
Max	1915.16	595.83	15439.12	1510.17	2105.88
% within expected range	41.5	18.9	18.5	22.4	65.3
% above expected max	58.5	59.4	61.3	53.9	N/A
% below expected min	N/A	21.7	20.2	23.7	34.7

Panel C

Correlation coefficient (R)	**Price Forecast**	**Recommendation Category**	**Expected Change**
Price Forecast	1	0.318	0.226
Recommendation Category	0.318	1	0.039
Expected Change	0.226	0.039	1

Table 7.8 provides a brief summary of the relationship between ratings and target prices for Irish and non-Irish brokers.

Table 7.8

Comparison of recommendation levels and target prices

The table presents the average of the 1-5 ratings attached to target prices (μ_T) and the average of the 1-5 ratings obtained by coding the overall recommendations (μ_R). The sample comprises the 41,688 pairs of contemporaneous target prices and recommendations. The z-scores relate to the difference in means with p-values in parentheses.

Broker	**# Obs**	μ_T	μ_R	**z-score**
Irish	12,622	3.97	4.34	39.2 (0.00)
Non-Irish	29,066	3.97	3.61	19.5 (0.00)
All	41,688	3.97	3.83	29.7 (0.00)

The evidence suggests that there is a pronounced disconnect between what brokers forecast and what they recommend. The difference in means is significant for all sets of brokers and it is clear that Irish brokers' recommendations tend to be more positive than their price forecasts. Overall, only approximately 38% of recommendations are in the category implied by the brokers' price forecast, with 36% (26%) above (below) the implied category.

The number of recommendations falling within the correct category is skewed upwards as both forms of output are biased upwards. There is also a bias in the number of recommendations falling below the minimum threshold of the implied category, as the top category contains approximately 37.5% of all recommendations. Any recommendation that incorrectly lies in this category must, by definition, be below the expected minimum price change. When the top category is excluded, only approximately 21% of recommendations fall into the 'correct' category based on the expected price change implied by brokers' price forecasts and 58% (21%) are above (below) the implied category[118]. The contrast between forecasts and recommendations is all the more stark when the output of Irish brokers alone is analysed, as can be seen in Table 7.9.

[118] The opposite bias is present in the lowest rating. However, there is such a small number of recommendations in this category (3.4% of the total) that omitting it does not materially alter the above results.

Table 7.9

Comparison of price forecasts and overall recommendations (Irish brokers)

The table compares contemporaneous target prices and recommendations for Irish brokers. The figures represent the percentage of each price forecast range (1-5) that fall into each of the five recommendation categories. The figures in bold on the diagonal are in the expected category, where the messages from the price forecast and overall recommendation are consistent.

N = 12,622		**Recommendation category**				
		1	**2**	**3**	**4**	**5**
Price forecast	**1**	**0.87%**	4.42%	14.75%	25.70%	54.26%
	2	0.00%	**12.64%**	23.58%	32.08%	31.70%
	3	0.00%	6.79%	**16.37%**	41.03%	35.81%
	4	0.09%	3.10%	12.78%	**31.30%**	52.73%
	5	0.09%	3.12%	13.02%	19.90%	**63.88%**

The percentage of recommendations in the expected category increases monotonically as the category becomes more positive. The proportion of recommendations falling within, above, and below is 18, 53, and 29%, respectively when the extreme categories (buy and sell) are excluded. The correlation coefficient between price forecasts and recommendation level is only 0.12. Perhaps the most striking finding is that Irish brokers issued buy recommendations in more than half of the cases where the stock was forecasted to decrease by more than 15% and issued positive recommendations in almost 80% of such cases.

These results are consistent with the arguments of Asquith *et al.* (2005), as discussed in section 4.4. It is clear that brokers are more willing to convey negative opinions of a firm's prospects via price forecasts. This preference may arise as issuing a price forecast below the current price of a firm is a less conspicuous form of pessimism and the trading implications for investors are more ambiguous. This veiled negativity is thus less likely to antagonise the covered firm.

It is apparent that an investor should either focus on a broker's price forecast or downgrade overall recommendation levels. The former approach provides a richer insight into an analyst's opinion as it is a continuous variable. Thus, one can distinguish between forecasts that fall into the same overall recommendation category. Furthermore, there are two problems with downgrading ratings. First, one cannot downgrade sell recommendations by one degree and second, if all ratings are downgraded it is no longer possible for brokers to communicate a buy recommendation.

7.4 EPS forecasts

This section analyses the accuracy of EPS forecasts. Figure 7.4 presents a comparison between actual and forecasted EPS for Irish and non-Irish brokers.

Figure 7.4

Average forecasted and actual EPS

The chart compares the EPS forecasts of Irish and non-Irish brokers with the subsequent actual EPS. The average EPS forecast for all firms with forecasts by both groups of brokers is calculated for each calendar year and compared to the realised EPS.

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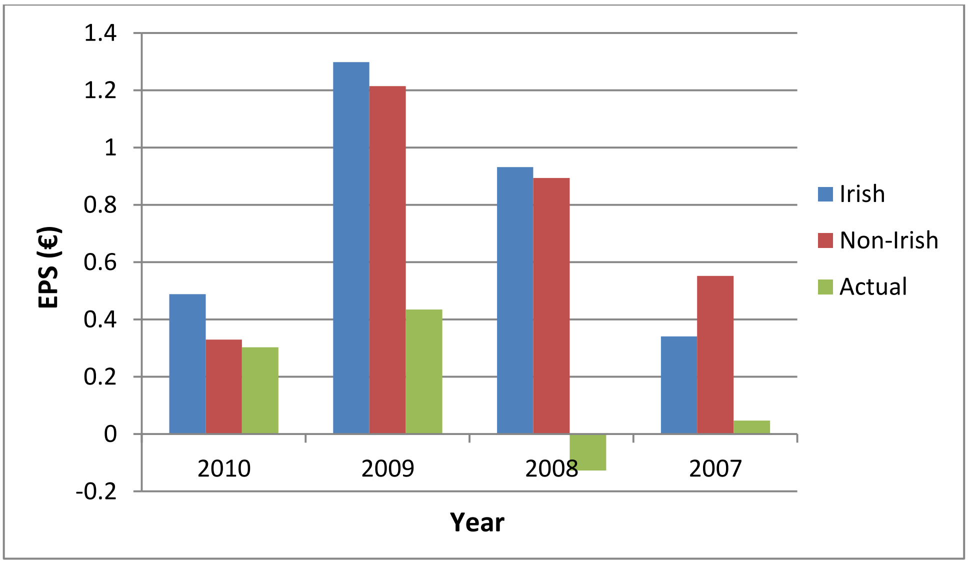


In stark contrast to the findings in relation to target prices and ratings, the average EPS forecast of Irish brokers is 5% lower than the non-Irish brokers. Irish brokers issued more optimistic EPS forecasts for only three of the 22 companies covered by both groups of broker. On average, Irish brokers revise EPS forecasts downwards by 6.6% of the current price, compared to a revision of 5.4% in the same direction for non-Irish brokers (t-statistic for difference in means = 3.72)[119].

The disconnect between price and earnings may suggest that Irish brokers use different valuation models than the other brokers. Alternatively, the findings are consistent with potential conflicts of interest. Irish brokers may issue more favourable price forecasts and recommendations in order to stimulate trading, while pitching their EPS forecasts at beatable levels in order to curry favour with covered firms and generate trading volume when earnings are announced. This may result in return continuation, as outlined in chapter four.

Furthermore, in contrast with the findings relating to price forecast, Irish brokers do not exhibit a tendency to herd their EPS forecasts to a significantly greater degree than non-Irish brokers. The coefficient of variation is calculated as the standard deviation of EPS forecasts scaled by the absolute value of mean forecasts (following Dische, 2002). The average dispersion for Irish brokers (0.54) is marginal lower than that of international brokers (0.59); however, the t-statistic for the difference in means is only 0.18.

7.5 Firm-specific attributes of recommended stocks

This section presents the findings relating to the relationship between recommendations and firm-specific variables and market returns. Jegadeesh and Kim (2006) document a positive relationship between current recommendations and lagged market returns. In order to assess whether this finding holds for the Irish market, the average recommendation rating ($\bar{A}_t$) is regressed against six-month lagged market returns (R_{mt}) as follows:

$$\bar{A}_t = \alpha + \beta R_{mt} + e_t \qquad (7.3)$$

The regression results are presented in table 7.10. It can be seen that Irish brokers tend to become more optimistic following good market performance to a greater extent than

[119] EPS revisions are scaled by price due to the relatively high frequency of negative EPS forecasts.

international brokers. The relationship was not significant at the 15% level in the case of non-Irish brokers. This suggests that Irish brokers may follow momentum strategies.

Table 7.10

Relationship between market returns and analyst recommendations

The table presents the regression coefficients (α and β) and correlation coefficient (r) with t-statistics in parentheses. The 432 average consensus weekly recommendation ratings are regressed against lagged six-month market returns. Significance at the 1% level is denoted by *.

Broker	α	β	p-value (β)	r
Irish	4.375 (481.9)	0.73* (2.80)	0.005	0.14 (2.80)
Non-Irish	3.683 (397.8)	0.38 (1.43)	0.152	0.07 (1.43)

The above approach uses market returns and provides a broad perspective on the relationship between analysts' output and macroeconomic indicators. The focus is narrowed in the following sub-sections by examining the firm-specific characteristics of stocks that analysts recommend favourably[120]. Subsequently, the relationship between each variable and future abnormal returns and volume is analysed. Appendix H presents summary statistics on each of the measures analysed.

7.5.1 Ratings vs. firm-specific attributes

Table 7.11 outlines the firm-specific attributes of stocks that analysts favour, based on the quintles discussed in section 5.4. Panel A details the averages for each variable sorted on the basis of ratings quintiles, while panel B presents average Spearman's rank correlation coefficients between each pair of variables.

[120] This section examines consensus recommendations. Individual recommendations are analysed in section 7.6.

Table 7.11

Ratings level and firm-specific characteristics

The table details the firm-specific attributes of stocks that analysts favour. Panel A details the average for each variable sorted on the basis of ratings quintiles, with quintile 5 containing the highest rated stocks. Panel B presents average Spearman rank correlation coefficients between each pair of variables.

Panel A: Average quintile values.

	1	**2**	**3**	**4**	**5**
Rating	3.203	3.727	4.026	4.342	4.762
Δ Rating	-0.206	-0.052	-0.004	0.072	0.162
Exp	50.73	33.14	22.70	21.56	17.78
Δ Exp	-9.13	7.10	1.84	3.24	-1.91
Mom(3)	-0.038	-0.007	0.009	0.061	0.142
Mom(6)	-0.005	-0.009	0.006	0.017	0.068
Vol	1.15	1.09	1.17	1.05	1.14
Size	21.17	21.17	20.81	20.66	20.54
B/M	0.994	0.599	0.491	0.540	0.448
E/P	12.798	13.269	16.280	18.269	14.389
Disp	1.222	1.158	1.177	1.101	1.118

Panel B: Mean Spearman's rank correlation coefficient.

	Rating	**Δ Rating**	**Exp**	**Δ Exp**	**Disp(P)**
Rating		0.226	-0.213	-0.041	-0.360
Δ Rating	0.226		-0.157	0.032	-0.069
Exp	-0.213	-0.157		0.201	0.005
Δ Exp	-0.041	0.032	0.217		-0.166
Mom(3)	0.227	0.102	-0.491*	-0.350**	-0.224
Mom(6)	0.128	0.083	-0.477*	-0.705*	-0.199
Vol	-0.069	0.021	-0.083	-0.106	0.010
Size	-0.222	-0.067	-0.007	-0.117	-0.015
B/M	-0.092	-0.140	0.445*	-0.065	-0.196
E/P	0.054	-0.054	-0.558	-0.132	-0.104

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

The results provide further evidence of severe optimism bias, as the mean consensus level of the bottom quintile is 3.20 (add). This is considerably higher than the equivalent figure of 2.76 (hold) in Jegadeesh *et al.* (2004). Although the sample periods differ (2000-2009 versus

1985-1998), it would be difficult to argue that the sample period employed in this thesis was one that justified such an elevated level of optimism.

The apparent inconsistency between analysts' recommendations and target prices, as outlined in section 7.2, is clearly in evidence again. Indeed, the expected price change suggested by analysts' price forecasts decreases monotonically as ratings become more favourable. The rank correlation coefficient between the two variables is -0.213. It seems that analysts attach higher ratings to stocks that they expect to increase to a smaller extent.

The firm-specific characteristics that are most highly correlated to analysts' recommendations are past returns (positive), size (negative), dispersion (negative) and book-to-market (negative). The positive correlation between ratings and past returns implies that analysts follow momentum strategies. Indeed, recommendations become monotonically more positive as past returns increase. This is the case for both past three- and six-month returns. This is consistent with the findings of Womack (1996), Jegadeesh *et al.* (2004), and Jegadeesh and Kim (2006). Separate analysis shows that the relationship between past returns and ratings is considerably stronger for Irish brokers.

There is a strong negative relationship between momentum and the expected price change implied by an analysts' target price. At first, this may appear surprising, as one would expect that analysts following momentum strategies will attach a higher target price to firms with higher momentum. However, if analysts do not revise their price targets then the expected price appreciation (and the revision thereof) will decrease as price increases.

There are strong negative relationships between size and dispersion and the four prediction measures. Ratings are a monotonically decreasing function of firm size and analyst disagreement. The dispersion variable shows that analysts tend to agree more about the prospects of high-rated stocks with existing positive momentum and smaller firms with low trading volume.

The negative correlation between past performance and dispersion may be caused by the non-synchronous response of analysts to bad news. Inertia in revising forecasts is likely to be more pronounced for poor performing stocks due to conflicts of interest and over-optimism of brokers as discussed in section 4.5. Such reluctance manifests itself in a high dispersion of forecasts.

Analysts also tilt towards firms with low volume and book-to-market ratios. However, these relationships are not as significant as those relating to momentum, size, and dispersion. The latter is consistent with the findings of Moshirian *et al.* (2009), who argue that conflicts of interest cause analysts to tilt their recommendations towards growth firms. Brokers appear to follow value strategies with reference to earning-to-price ratios, with ratings generally becoming more favourable as E/P ratios increase. However, the relationship is not monotonic, as the E/P ratio of the top rated stocks (quintile 5) is lower than that of quintiles 3 and 4. It seems somewhat contradictory that analysts appear to be momentum traders vis-à-vis past returns and book-to-market ratios but are contrarian (value) investors in relation to price-earnings ratios and volume.

7.5.2 Future returns

This section examines the value of brokers' output by estimating the future abnormal returns to quintiles based on the four measures of analysts' opinions. For comparison purposes, abnormal returns to quintiles sorted on each of the firm-specific characteristics are also computed. Table 7.12 presents the three-month (panel A) and six-month (panel B) abnormal returns to each quintile. The final column in each panel shows the average correlation coefficient between each variable and future market-adjusted abnormal returns.

The returns in the penultimate column represent the difference between the abnormal returns of the two extreme quintiles. The strategies adopted by brokers, as outlined in the previous section, are used to determine whether such abnormal returns are calculated as high-minus-low or *vice versa*. In other words, the table tests the effectiveness of the strategies that brokers appear to follow on average[121]. Abnormal returns by quintile are shown in graphical form in figure 7.5.

Table 7.12

Returns to quintile trading strategies

The table presents the three-month (Panel A) and six-month (Panel B) abnormal returns to each quintile. The final column in each panel shows the average correlation coefficient between each variable and future abnormal returns.

Panel A: Three-month abnormal returns							
	1	**2**	**3**	**4**	**5**	**Profit**	**r**
Ratings	0.016	0.021	0.001	0.016	0.033	0.016	0.030
∆ Rating	0.005	-0.007	0.010	-0.011	0.063	0.058	0.036
Exp	0.000	0.007	0.045	0.023	0.002	0.002	-0.134
∆ Exp	0.021	-0.001	0.011	-0.020	0.044	0.023	-0.077
Mom(3)	-0.034	0.025	0.009	0.042	0.051	0.086	0.052
Mom(6)	-0.027	0.007	0.027	0.027	0.056	0.084	0.032
Size	0.024	0.046	0.047	0.012	-0.039	0.063	-0.234
Disp	0.025	-0.020	0.013	0.013	0.031	-0.006	-0.078
Vol	0.006	0.013	0.020	0.036	0.024	-0.018	-0.065
B/M	-0.021	0.023	0.046	0.030	0.072	0.092	-0.029
EP	0.061	0.008	0.009	0.017	0.005	-0.056	-0.178

Panel B: Six-month abnormal returns							
	1	**2**	**3**	**4**	**5**	**Profit**	**r**
Ratings	0.067	0.046	-0.003	0.032	0.062	-0.005	0.028
∆ Rating	0.039	0.008	0.007	0.000	0.085	0.047	0.030
Exp	0.019	0.032	0.072	-0.002	0.025	0.007	-0.171
∆ Exp	0.048	0.009	0.039	-0.014	0.021	-0.027	-0.159
Mom(3)	0.013	0.040	0.027	0.073	0.075	0.062	0.085
Mom(6)	0.015	0.026	0.032	0.051	0.096	0.081	0.026
Size	0.086	0.086	0.110	0.019	-0.074	0.160	-0.351**
Disp	0.027	-0.024	0.008	0.069	0.046	-0.019	-0.050
Vol	0.029	0.036	0.050	0.070	0.049	-0.020	-0.070
B/M	-0.020	0.044	0.105	0.031	0.165	0.185	-0.046
EP	0.123	0.033	0.038	0.025	0.019	-0.104	-0.205

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

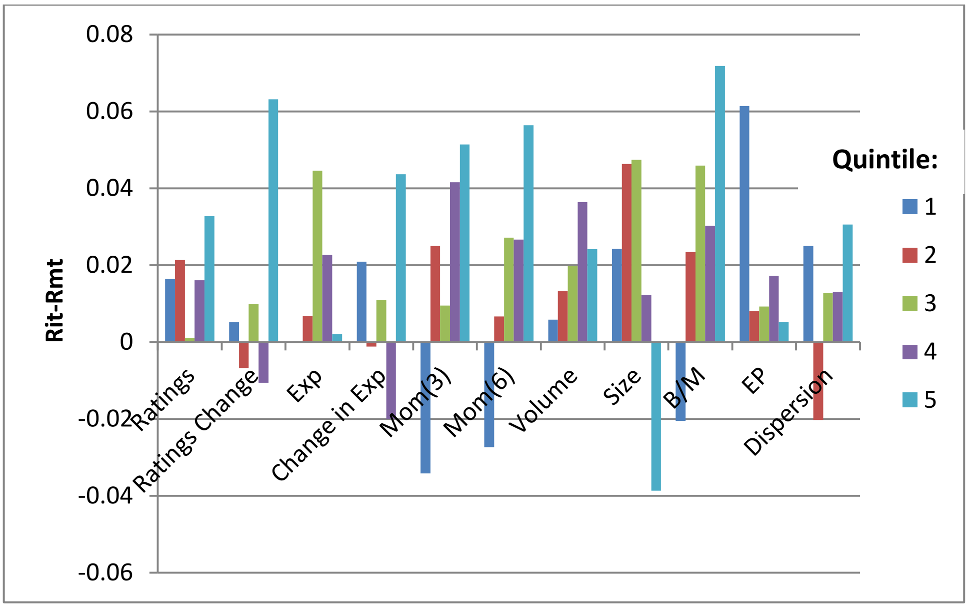
[121] Low-minus-high returns are calculated for size, dispersion, volume, and B/M. The remaining variables are calculated in the opposite manner.

Figure 7.5

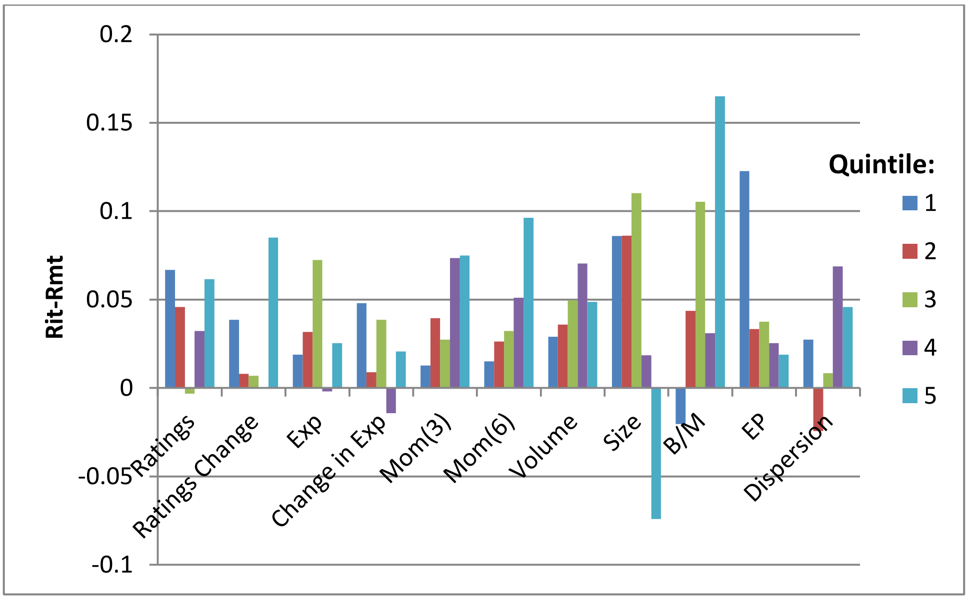
Abnormal returns vs. firm-specific characteristics

The charts present the future three- and six-month market-adjusted abnormal returns for quintiles formed on each of the firm-specific variables described in section 7.5.

Panel A: Three-month abnormal returns



Panel B: Six-month abnormal returns



Future returns are generally an increasing function of ratings, with the top-rated stocks earning the highest market-adjusted returns over the next three and six months. However, a strategy of buying (short selling) the highest (lowest) rated stocks only generates moderate abnormal returns and the quintile of the lowest rated stocks outperforms top-rated stocks over a six-month period. The correlation between past and future returns suggests that the correlation between ratings and future returns may simply be due to momentum rather than skill, as analysts lean towards stocks with positive momentum. The high momentum returns are consistent with the findings presented in the previous chapter. Abnormal returns over six months monotonically increase for quintiles based on existing six-month momentum and future abnormal returns are highest to quintile 5 for all four combinations of past and future returns. However, consistent with the findings reported in section 6.3, a three-month holding period generates higher abnormal returns.

Consistent with Jegadeesh *et al.* (2004), there is a marked difference between the abnormal returns to recommendation levels and revisions, with the latter generating abnormal returns of 5.8% in the three months following the quarter end, compared to 1.6% for recommendation levels. The superior performance of revisions is entirely derived from the returns of extreme upgrades. In fact, short selling stocks with the most extreme downgrades would result in losses, as such stocks outperform the market over the next quarter, as was the case with ratings levels. However, such losses are greater when rating levels are used[122].

It is not surprising that recommendation changes outperform recommendation levels as the latter are more likely to be stale at the end of the quarter when they are evaluated using the above framework due to the lack of revisions. As discussed in section 7.2, recommendations remain unchanged for an average of 41 weeks. In contrast, recommendation changes cannot be more than 13 weeks old and the average change will be approximately seven weeks old, *ceteris paribus*.

[122] It is not clear than an investor would short sell the lowest rated stocks as only a small proportion of such stocks attracted sell ratings. A more straightforward strategy of buying top-rated stocks generates more significant abnormal returns.

Although brokers exhibit greater selection and timing ability when changes in recommendations are evaluated, it still appears that they fail to outperform growth strategies based on momentum, B/M, and size. The abnormal returns to the high book-to-market quintile are the highest of any of the 55 quintiles. Furthermore, the returns to quintile 1 are negative, adding further weight to the validity of a growth strategy based on this ratio.

Size, B/M, and the two momentum measures are the only indicators where the returns to both of the extreme quintiles are of the hypothesised sign for three-month abnormal returns. The negative relationship between size and future returns is the only statistically significant relationship at the five per cent level. Value strategies based on B/M and size generate abnormal returns of 18.5 and 16% respectively in the six months following the end of the calendar quarter. These results are consistent with the findings of Banz (1981) and Fama and French (1992). However, they directly contrast with the results of Jegadeesh *et al.* (2004), who report that large firms outperformed small firms and that value firms did not outperform growth firms.

Recall that brokers follow value strategies in terms of E/P ratios. However, there is a strong negative correlation between such ratios and abnormal returns; in other words, growth/momentum strategies are profitable. This contrasts starkly with the findings of Basu (1977) and Jegadeesh *et al.* (2004). As outlined above, the relationship between analysts' ratings and past returns, price-earnings ratios, and book-to-market ratios paints an inconsistent picture in terms of whether analysts favour value or growth strategies. There is also some discrepancy in the relationships between these three variables and future returns; value (growth) strategies are profitable when formed on the basis of B/M ratios (momentum and E/P ratios).

The finding that returns are generally an increasing function of past volume is diametrically opposed to the results of Jegadeesh *et al.* (2004). Recall that Lee and Swaminathan (2000) argue that low (high) volume stocks are exhibit value (glamour) characteristics. Accordingly, the superior returns to high-volume stocks can be viewed as consistent with momentum/glamour returns and contradict the finding of Lee and Swaminathan (2000) that firms with high past turnover earn lower future returns.

The negative correlation between dispersion and future returns is consistent with the findings of Erturk (2006) and Dische (2002) but starkly contrast with Verardo (2009) and Doukas and McKnight (2005). The results suggest that momentum is partially attributable to analyst herding. However, the relationship is not statistically significant and the quintile of high-dispersion stocks outperforms the low-dispersion quintile.

7.5.3 Abnormal volume

It is of interest to examine whether analysts' output is correlated with future abnormal volume in order to assess whether analysts induce trading activity. Table 7.13 presents details of abnormal volume for quintiles sorted on recommendation levels and presents analogous statistics for all other firm-specific variables.

Table 7.13

Abnormal volume

The table details the abnormal volume ratios for quintiles formed on each of the first-specific characteristics. Abnormal volume is calculated by scaling the volume for the quarter following recommendations by the average volume for three quarters prior to the recommendation quarter. The last column shows the average correlation coefficient (r) between each variable and future abnormal volume.

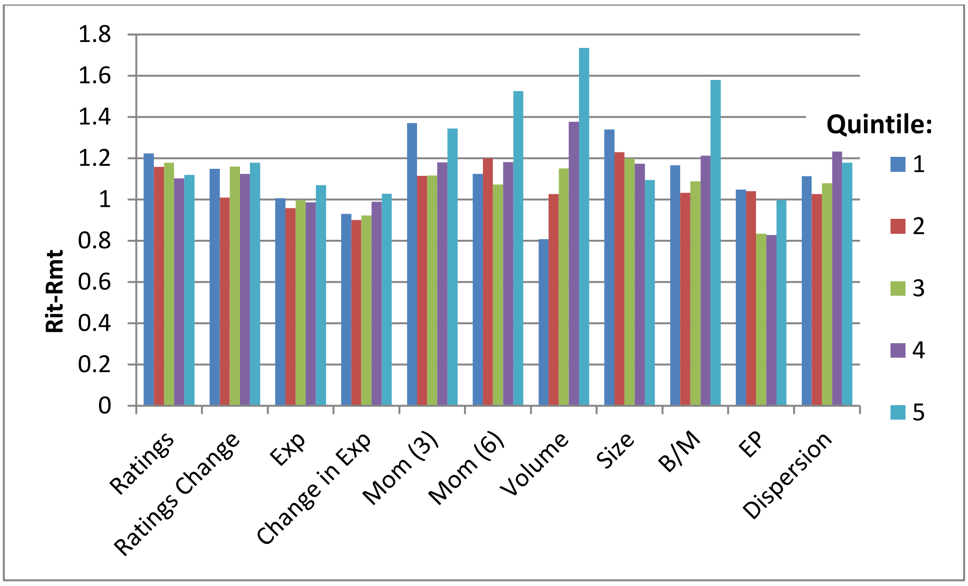
	Quintiles					
	1	**2**	**3**	**4**	**5**	**r**
Rating	1.223	1.158	1.177	1.101	1.118	-0.048
∆ Rating	1.148	1.009	1.159	1.123	1.178	-0.029
Exp	1.006	0.958	0.994	0.986	1.070	-0.075
∆ Exp	0.931	0.901	0.922	0.989	1.028	0.014
Mom(3)	1.370	1.114	1.116	1.180	1.344	-0.106
Mom(6)	1.123	1.200	1.072	1.182	1.524	-0.091
Size	1.338	1.228	1.198	1.173	1.094	-0.037
Disp	1.113	1.027	1.078	1.232	1.178	-0.040
Vol	0.807	1.025	1.150	1.376	1.735	0.407
B/M	1.165	1.032	1.088	1.211	1.580	-0.095
E/P	1.047	1.039	0.834	0.828	0.997	-0.149

There is no discernible relationship between the four prediction measures and future volume, suggesting that analysts' recommendations do not generate abnormal volume. Surprisingly, it is the lowest rated stocks that generate the highest level of abnormal volume. This would be expected if investors acted on such relatively negative ratings by selling stocks in greater quantities than would be the case for purchases of high-rated stocks, in recognition of analysts' conflicts of interest. However, such stocks earn the highest return of any quintile of stocks over the subsequent six months. Figure 7.6 presents the future standardised volume to quintiles based on each of the firm-specific variables described in section 7.5.1.

Figure 7.6

Future abnormal volume

The chart presents the future standardised volume to quintiles based on each of the firm-specific variables. Abnormal volume is calculated by scaling the volume for the quarter after recommendations by the average volume for three quarters prior to the recommendation quarter.



Abnormal volume decreases monotonically with firm size. This is consistent with the finding that smaller firms generate higher abnormal returns. Abnormal volume is generally an increasing function of past momentum and is a monotonically increasing function of past volume. The latter relationship may be driven by the former; in other words, high past returns are associated with high past volume. Momentum means that past and future returns are related and this in turn induces a positive relationship between past and future volume.

Taken together, the above evidence strongly indicates that analysts favour small firms with high momentum and low book-to-market ratios. It appears that brokers are vindicated in the use of momentum strategies but not in their use of value strategies vis-à-vis B/M and EP, which underperform stocks at the opposite end of the valuation spectrum by 10.4 and 18.5%, respectively, over the six months subsequent to the calendar quarter end. It is also clear that recommendation revisions add greater incremental value than recommendation levels.

All forms of brokers' output generate lower returns than relatively straightforward strategies based on size, momentum, and book-to-market. The finding that analysts fail to add significant value confirms the results of Jegadeesh *et al.* (2004) for the US. Table 7.14 summarises the hypothesised and actual relationships between each firm-specific variable and future abnormal returns and volume.

Table 7.14

Summary of relationships

The table presents the hypothesised and actual relationships between each of the firm-specific variables and brokers' ratings and abnormal returns. The second column details the hypothesised direction of the relationship between each variable and abnormal returns based on existing literature. The third column shows the relationship between each variable and the brokers' ratings and the last column lists the direction of the relationship between each firm-specific attribute and future abnormal returns.

Variable	Hypothesised relationship	Ratings	Abnormal returns
Momentum	+	+	+
Size	-	-	-
Dispersion	-	-	-
Volume	-	-	-
Book-to-market	+	-	-
Earnings-to-price	+	+	-

7.6 Micro-level analysis

The above sections examine consensus ratings at the start of each quarter. In contrast, this section examines recommendation revisions on a continual basis and does so at the level of each broker rather than at the consensus level. In other words, we move from a calendar-time to an event-time approach. The latter has the advantage of increasing the number of observations and thus the power of statistical tests. However, the approaches tested here may not represent implementable strategies due to the need for frequent rebalancing[123].

Another key difference is that this section examines portfolios that are clearly defined in terms of the recommendation level. The extreme portfolios in the previous section could not be interpreted as 'buys' or 'sells', as they were formed on the basis of quintiles. Given the dominance of buy recommendations the top-rated quintile almost exclusively contains buy recommendations. However, the lowest quintile could not be exclusively comprised of sell recommendations, as such recommendations accounted for less than 3% of all advice.

Furthermore, this section allows one to differentiate between the market response to different types of revisions. The hypothesised direction of any market reaction is not straightforward as the implications of some revisions are unclear. For example, downgrades from buy to add are included as a downgrade in the quintile-based approach. However, the new recommendation level remains positive[124].

This section focuses on recommendation revisions, as opposed to levels, for a number of reasons. First, as outlined in section 7.2, recommendation levels remain unchanged for extended periods of time. Second, analysts display a marked tendency to herd. These characteristics of the data increase the likelihood of encountering problems associated with cross-sectional dependence and serial correlation. This problem is largely caused by

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[123] However, it seems more plausible that investors would implement trades as close as possible to the announcement of recommendations or revisions rather than at the end of each calendar quarter. It also seems more likely that investors would follow a small number of brokers rather than the consensus recommendation level.

[124] Furthermore, the theoretical impact of revisions to the hold category is questionable as the destination category does not recommend any action on the part of the investor. However, it may be suspected that a downgrade to hold may have a greater impact if holds are thinly-veiled sell recommendations.

overlapping observations and becomes more germane when extended test periods are employed. Such problems are largely alleviated by using recommendation revisions. A novel approach is adopted to mitigate the remaining problems caused by overlapping observations, as discussed in the next sub-section. Third, as reported in section 7.5, recommendation revisions have more predictive power than recommendation levels. It is probable that recommendation levels are less profitable as a large proportion of such ratings are stale as brokers leave recommendation levels unchanged for extended periods.

Recommendations are favoured over price and EPS forecasts. Recommendation ratings provide a clear signal to the market and represent the principal form of communication between brokers and investors in this sample, accounting for in excess of half of brokers' output. Furthermore, it is not possible to accurately calculate EPS revisions when such forecasts take a negative value. A significant number of forecasts fall into this category in the later years of the sample.

7.6.1 Price effects

This section examines the stock picking and timing abilities of brokers by measuring the price impact of revisions for each of the revision categories based on the original and new recommendation. Existing research tends to examine a small number of revision categories and holding periods. This study examines 20 revision categories and tracks abnormal returns on a continual basis.

A central task in any event study is to strike a balance between accurately representing an investor's trading experience and statistical-significance considerations. Independence assumes that the abnormal returns of firms are independent in time-series and cross-section (Kothari and Warner, 2006). Cross-sectional and serial dependence are often encountered when dealing with panel data and can result in biased test statistics[125]. This study accounts

[125] For a discussion of the impact of such dependence, see, for example, Brown and Warner, (1980); Mitchell and Stafford, (2000).

for overlapping revisions in a manner that more accurately reflects an investor's experience and minimises cross-sectional dependence.

Robustness tests in this study show that failing to account for overlapping revisions results in considerably inflated abnormal returns and test statistics, as the number of independent observations is overstated. Accordingly, abnormal returns and volume will be calculated using non-overlapping returns in order to minimise cross-sectional dependence issues.

Overlapping revisions are accounted for in two principal ways. First, contemporaneous revisions of the same type that are made by multiple brokers for a particular company are treated as one observation. Second, if there is a further revision before the end of an event period over which abnormal returns are measured returns are curtailed so that they do not overlap[126]. Returns are calculated for the entire test period only if there are no subsequent revisions during this time.

It is felt that this approach strikes the optimum balance between investor-experience and statistical-significance concerns. For example, it seems reasonable to expect that if a stock experiences a subsequent reversal by the same broker before the end of the event window, an investor will revise their trading strategy. Similarly, if multiple brokers issue contiguous revisions to buy the same stock it seems implausible that an investor would buy the same stock multiple times over a short space of time and sell each holding in consecutive weeks one year hence.

Market-adjusted buy-and-hold abnormal returns are estimated as the difference between the product of one plus the company returns (R_{it}) over various time periods minus the equivalent market return (R_{mt}), as is the conventional approach in studies of brokers' advice (for example, Ryan, 2006; Jegadeesh *et al.*, 2004)[127].

[126] This also facilitates a comparison with previous research relating to the Irish market, as Ryan (2006) excludes from further analysis firms that incur a reverse revision after the recommendation month.

[127] Several studies (for example, Desai *et al.*, 2000) measure abnormal returns with reference to a control firm. However, this approach is not deemed appropriate for this study, as the small number of companies on the Irish market means that it not always possible to find a non-event control firm for any reasonably long test period.

$$BHAR_{it} = \prod_{t=0}^{T}(1 + R_{it}) - \prod_{t=0}^{T}(1 + R_{mt}) \qquad (7.4)$$

The number of overlapping revisions increases for longer test periods. Accordingly, equation 7.14 is recalculated for holding periods of increasing lengths, commencing at week -26 and terminating at week +52 relative to the revision date. Abnormal returns are averaged across *n* unique revisions of a specific type experienced over the sample period of approximately ten years to give the equally-weighted portfolio abnormal return ($\overline{AR}_t$):

$$\overline{AR}_t = \frac{1}{n}\sum_{i=1}^{n} BHAR_{it} \qquad (7.5)$$

This procedure is repeated for each of the 20 revision categories i.e. add to buy, hold to add, etc. The statistical significance of average abnormal returns is estimated by:

$$t = \frac{\overline{AR}_t}{SE_T} \qquad (7.6)$$

Where SE_T is the cross-sectional standard error of abnormal returns. Table 7.15 presents details of the number of recommendations in each of the 20 revision categories after overlapping revisions are excluded.

Table 7.15

Number of recommendation revisions by category

The table details the number of revisions sorted by the pre- and post-revision categories. The original sample of 1,094 was reduced to 1,043 after cases where simultaneous revisions of the same type and revisions without the necessary return and volume data were excluded.

	N = 1,043	New Buy	New Add	New Hold	New Reduce	New Sell	Total	%
Original	Buy		152	174	10	7	343	33
	Add	153		97	21	2	273	26
	Hold	155	77		44	38	314	30
	Reduce	9	18	31		9	67	7
	Sell	6	1	34	5		46	4
	Total	323	248	336	80	56	1,043	-
	%	31	24	32	8	5	-	100

The sample contains 489 (47%) upgrades and 554 (53%) downgrades. Table 7.16 details the average abnormal returns to each of the revision categories.

Table 7.16

Abnormal returns to revisions

Panel A presents the cumulative buy-and-hold market-adjusted abnormal returns for each of the 20 revision categories for week 0-4. Panel B details the returns to upgrades and downgrades for various holding periods relative to week 0.

Panel A

		New Buy	New Add	New Hold	New Reduce	New Sell
Original	Buy		-0.002	-0.011	-0.150	0.031
	Add	0.024*		-0.036*	-0.016	-0.126
	Hold	0.024*	0.038*		-0.063*	-0.029
	Reduce	-0.018	0.014	0.009		0.021
	Sell	0.059	0.059*	-0.002	0.009	

Panel B

Category	-26 to 0	0	0-26	0-52
Upgrades	0.022**	0.007	0.038*	0.071*
Downgrades	0.020	-0.021*	-0.008	-0.002

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

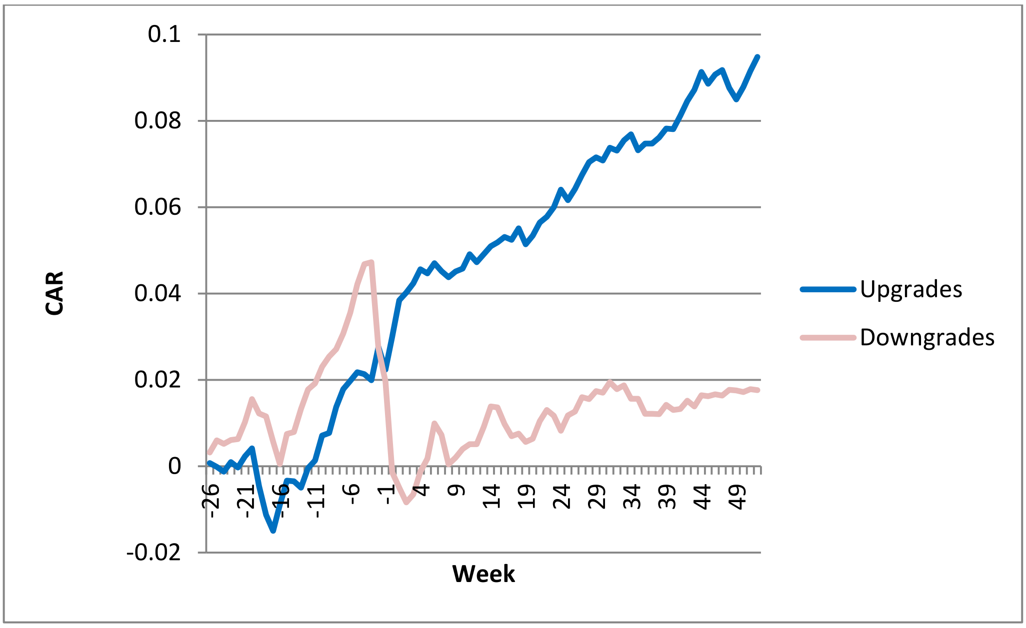
Table 7.16 shows that there is a generally a stronger response to upgrades. This is not surprising, as short-sale constraints may limit the market response to negative ratings. Surprisingly, the market response is less pronounced for revisions of larger degrees. It is found that 64.5% (53.4%) of upgrades (downgrades) generate positive (negative) abnormal returns over the 0-52 week period. The percentage for upgrades is larger than the equivalent figure of 54% reported in Desai *et al.* (2000). It should be noted that the relatively low number of revisions to sell reduces the statistical significance of abnormal returns to such downgrades. For example, the -12.6% generated by revisions from add to sell is the average of only two such revisions.

The returns to various revision categories are analysed on a week-by-week basis in graphical form. These graphs plot cumulative abnormal returns from 26 weeks before to 52 weeks after revisions as it is of interest to compare pre- and post-revision returns. Appendix I contains separate graphs for the pre- and post-revision stage for some of the key revision categories. The analysis commences with the general cases of upgrades and downgrades, before focusing on some of the specific revision categories with significant abnormal returns.

Figure 7.7

Abnormal returns to revisions

The graph plots the cumulative abnormal returns to upgrades and downgrades relative to week -26. Revisions are sorted based on the original and new category and abnormal returns are calculated by taking the raw returns on each firm minus the market return. Such abnormal returns are averaged across all firms experiencing each type of revision over the sample period of June 2000 to December 2010.



The market response to upgrades is considerably more striking than the reaction to downgrades, with a statistically significant average abnormal return of 7.1% (t = 4.01) in the year following upgrades. The average cumulative abnormal return to upgrades is not significant in week 0 but becomes significant one week after the revision week and remains so for all of the remaining weeks up to week 52. Returns remain significantly negative for downgrades for approximately four weeks. In the longer term, downgrades generate positive returns. However, such returns are not economically or statistically significant[128].

Taken together, the above results suggest that the market responds relatively quickly to downgrades but there is significant drift following upgrades. Assuming that upgrades and downgrades are associated with good and bad news respectively, this contradicts the existing

[128] Average abnormal returns for downgrades are 1.76% (t = 1.30).

information-diffusion literature (for example, Frazzini, 2006; Hong *et al*., 2000), which implies that bad news travels slowly and good news travels fast. Indeed, it could also be said that the market overreacts to downgrades, as abnormal returns following such revisions rebound after an initial period of negative returns.

These findings are thus consistent with McQueen *et al.* (1996) and Ashley (1962), who show that stock prices react more quickly to bad news than good news. However, they contrast with those of Womack (1996), who finds that the majority of the price impacts to buy recommendations are observed in the three-day period surrounding the recommendation; whereas abnormal returns persist for up to six months for sell recommendations. The findings also starkly contrast with those of Jegadeesh and Kim (2006) and Moshirian *et al.* (2009), who report that long-term abnormal returns to upgrades are insignificant, while returns to downgraded stocks drift in the majority of the markets in their sample of G7 and emerging markets, respectively.

Alternatively, the drift in upgrades may arise as investors are sceptical about such positive revisions in light of analysts' conflicts of interest. Downgrades are acted upon much quicker, as investors assume that analysts must have strong information in order to overcome the negative reaction of the covered firm that may ensue. This is consistent with the findings of McKnight and Todd (2006), Malmendier and Shanthikumar (2007), and Morgan and Stocken (2003), who report that investors downgrade recommendations in recognition of conflicts of interest, as outlined section 4.5.3.

There are significant abnormal returns for upgrades in the four to five months prior to revisions. This is consistent with the findings of Aitken *et al.* (2000), and Bauman *et al.* (1995) and connotes that brokers either follow momentum strategies or react in an extremely delayed fashion to the good news that may have driven such positive returns. However, the positive drift in the returns of upgraded stocks persists for such an extended period that brokers' revisions contain value, although the timing of their revisions is imprecise.

Similarly, downgrades experience large negative abnormal returns prior to the revision date. However, such abnormal returns persist for a shorter period prior to revision when compared to upgrades. It appears that brokers downgrade stocks in a more timely fashion. However, the negative drift in returns persists for a relatively short time in the post-revision period. Therefore, the relatively short delay in brokers revising their forecasts renders such revisions largely unprofitable. It appears that it requires more stock-picking and timing ability to profitably revise recommendations downwards as the window of opportunity to profit is considerably narrower.

To some extent, these findings contradict Ryan (2006), who reports that returns are significantly negative in the six months prior to the initiation of sell recommendations. Furthermore, Ryan (2006) finds that there is no drift for buy recommendations but a significant drift for sell recommendations. Such findings directly contrast with the pattern of cumulative returns presented in figure 7.7. However, the sharp decline in the cumulative returns of downgraded stocks shortly prior to the revision week is consistent with Ryan (2006), who finds that largest negative returns to sell recommendations occur in the month before initiation.

The large abnormal returns to upgrades relative to downgrades are largely attributable to the economic value of upgrades issued by Irish brokers. Such revisions generate average abnormal returns of 4.2% (t = 2.06) over the 0-26 week period, compared to 1.6% (t = 1.43) for non-Irish analysts. The abnormal returns to downgrades are insignificant for both broker groups. Further analysis shows that abnormal returns are higher for brokerage firms that follow more firms[129] and for firms that are relatively neglected. The superior performance of Irish brokers may thus be partially explained by the finding of Ryan (2006) that individual analysts at Irish brokerage firms tend to cover more sectors than their US or UK counterparts.

[129] This contradicts the findings of Clement (1999) and Jacob *et al*. (1999), as outlined in section 4.3. However, the correlation may be spurious as it may capture the superior performance of Irish brokers, who tend to issue a disproportionately large proportion of recommendations.

The more persistent drift in upgrades is consistent with the findings reported in section 6.2 that the momentum returns in Ireland were dominated by the winner portfolio. Upgraded stocks are more likely to be past winners given analysts' tendency to follow momentum strategies. Again, this suggests that the superior performance of Irish brokers principally arises from the exploitation of return continuation. Indeed, the abnormal returns to upgrades are similar to the returns to the winner portfolio, as outlined in section 6.2.

It is of interest to further examine the dynamics of returns following revisions by examining the share-price reaction to specific categories of revision based on the pre- and post-revision recommendation levels. As expected, the market reacts to the greatest degree to revisions that move the recommendation category to or from positive or negative ratings. For example, downgrades from hold to reduce elicit a greater response to those from buy to add.

Consistent with the existing literature, the market reaction of downgrades from positive to negative ratings is considerably larger and more statistically significant than that of revisions from negative to positive ratings. However, the opposite is the case when the sample is limited to revisions to the extreme ratings. As expected, there is virtually no reaction to upgrades to hold. Consistent with Ryan (2006), there is some evidence that a hold may be a negative recommendation by another name, as revisions from buy and add to hold yield negative post-revision abnormal returns. Figure 7.8 plots the cumulative abnormal returns to a number of key revision categories.

Consistent with figure 7.7, the abnormal returns to each type of upgrade drift to a greater extent than those of downgrades. The returns to downgrades from add are all negative and statistically significant in the four weeks prior to such revisions. Subsequent returns are negative for all three revision categories for approximately six months after such recommendation changes. The pattern for downgrades from buy to the other four categories is less clear, and somewhat surprisingly, the only statistically significant returns are the positive returns to downgrades from buy to sell.

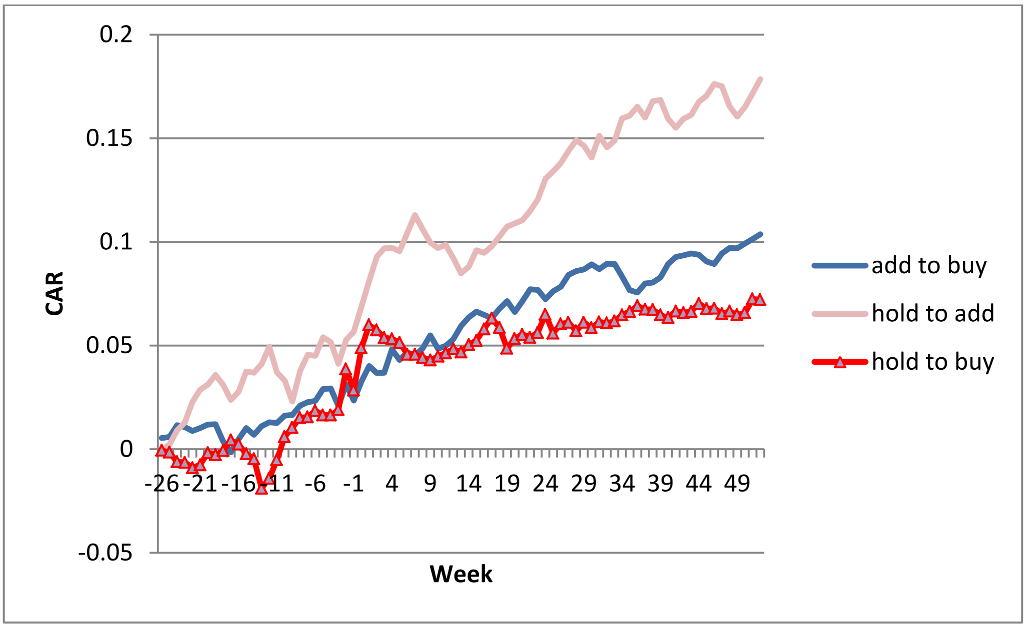
There is also a marked dichotomy between upgrades from the extreme rating and those from other ratings. The most statistically and economically significant returns are generated for upgrades from hold and add. The returns prior to the revision dates also tend to be more significant for such upgrades. Surprisingly, none of the four categories where ratings are upgraded from negative to positive generate economically and statistically significant abnormal returns in the post-revision period.

Figure 7.8

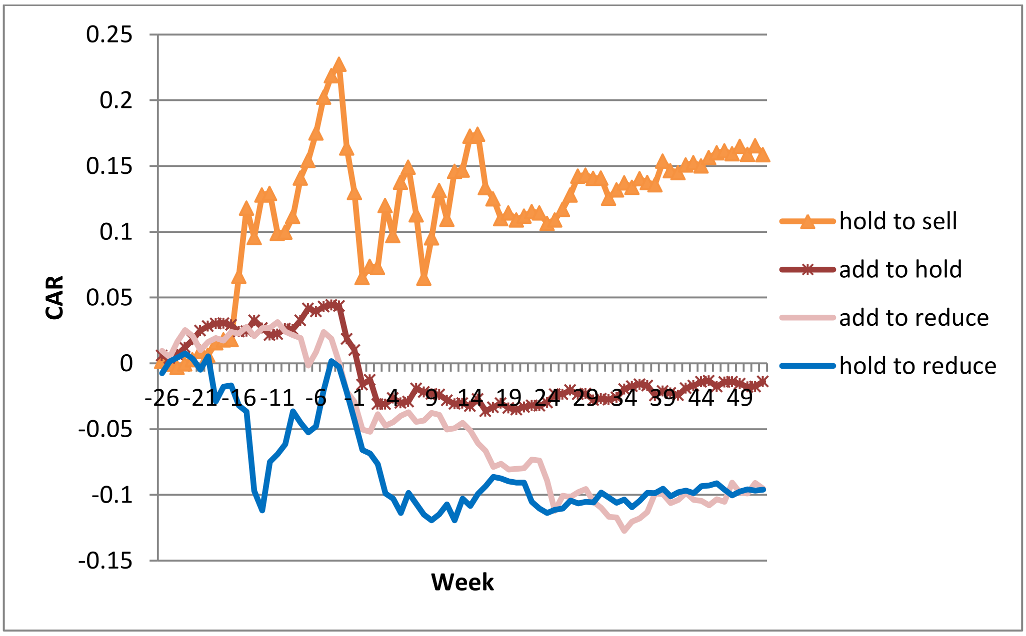
Abnormal returns to key upgrades and downgrades

The graphs plot the cumulative abnormal returns relative to week -26 for a number key upgrades and downgrades.

Panel A: Key upgrades



Panel B: Key downgrades



Revisions of smaller degrees generate more significant abnormal returns, in direct contrast with the findings of Ho and Harris (1998) and Stickel (1995). This finding may be explained by return continuation. If momentum plays a central role in predicting future returns then it is less likely that larger revisions will be prophetic as they are swimming against the tide of momentum (assuming that the original recommendation category was informative).

7.6.2 Volume effects

Section 7.5 concluded that brokers' output did not induce significant trading volume. However, the earlier findings were derived using consensus forecasts at the end of each calendar quarter. This section allows for a more precise assessment of any volume impact by examining revisions in event time. Furthermore, the analysis is conducted at the level of individual brokers and a distinction is made between revisions to and from each of the five recommendation categories.

Following Jegadeesh and Kim (2006), abnormal volume is analysed by calculating standardised volume (SV), which is the ratio of volume in an event week to the average volume over an extended period before and after the event window. The event window runs from eight weeks before to eight weeks after a recommendation revision, while average volume is calculated using data from 26 weeks before and after the event window.

$$SV_t^i = \frac{Volume_t^i}{\frac{1}{52} * \left(\sum_{\tau=-34}^{-9} Volume_\tau^i + \sum_{\tau=9}^{34} Volume_\tau^i\right)} \qquad (7.7)$$

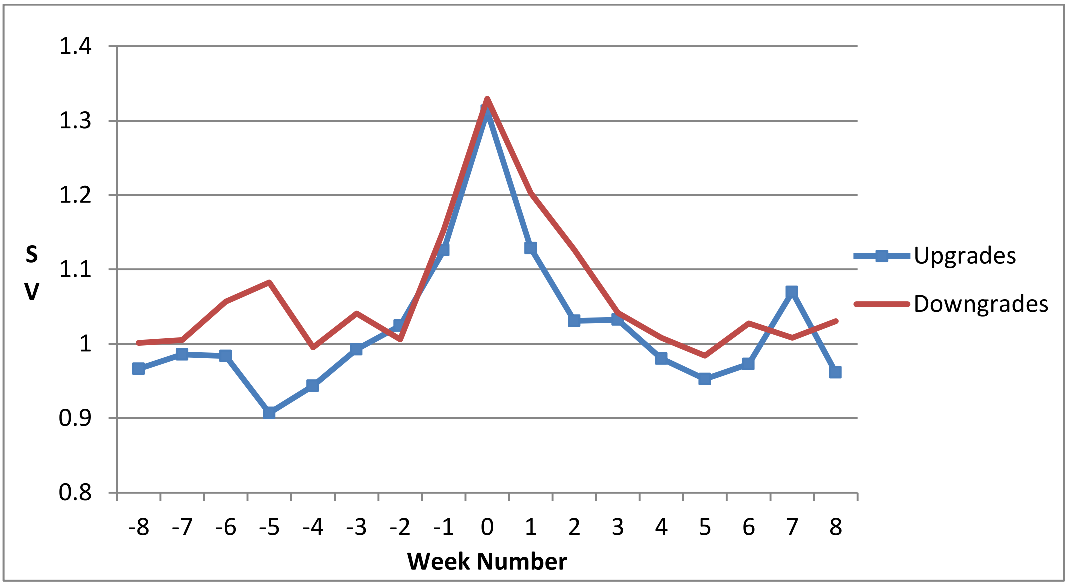
Where $Volume_t^i$ is the number of shares traded in week *t*. Standardised volume is calculated for each of the 20 revision categories for each week of the event window. Abnormal volume is indicated by a standardised volume figure that is significantly different from one[130]. Figure 7.9 plots the standardised volume for upgrades and downgrades for eight weeks before and after the revision date.

[130] Following Jegadeesh and Kim (2006), observations with standardised volume in excess of 30 are excluded.

Figure 7.9

Standardised volume

The figure charts standardised volume for each of the 17 event weeks. Standardised volume is computed as the ratio of volume in each event week to average long-term volume.



Standardised volume for upgrades is statistically different to one in weeks -1 to +1. Abnormal volume for downgrades is significant for an additional week (t +2). This contradicts the findings in section 7.6, as it suggests that investors react in a more delayed fashion to bad news. However, the event window in equation 7.7 may be overly restrictive, as abnormal returns persist for upgrades for up to one year. Accordingly, the denominator may be inflated by the associated increase in volume, thereby dampening the extent of abnormal volume.

The standardised volume for upgrades and downgrades in week 0 is 1.31 (t = 6.58) and 1.32 (t = 7.96), respectively. These levels of abnormal volume are significantly lower than those reported in Jegadeesh and Kim (2006) for the US (1.67 and 2.3, respectively). The abnormal volume for revisions to extreme ratings is also considerably lower than in the existing literature. For example, Womack (1996) reports ratios of 1.9 and 3 for revisions to buy and sell revisions, respectively. The equivalent figures for this dataset are somewhat lower at 1.26 and 1.33, respectively[131].

Abnormal volume is statistically significant for both upgrades and downgrades prior to the revision date. It might be tempting to conclude that this suggests that details of upcoming revisions are leaked to certain clients prior to the revision date. However, there is another possible explanation for this finding. Brokers may be slow to revise their recommendation levels after firms release price-sensitive news. Investors may trade aggressively on such news in advance of the broker's revision. This appears more plausible as the abnormal volume response to downgrades is more significant in the pre-revision phase. Conflicts of interest may cause brokers to be more reluctant to revise their recommendations following bad news.

A detailed breakdown of standardised volume by revision category is provided in appendix J. In general, abnormal volume is more significant for revisions to positive categories. There is no statistically significant abnormal volume in week 0 for approximately half of the revision categories, the majority of which are downgrades. This confirms the findings in the previous section that analysts' output does not have a significant impact on volume.

7.7 Conclusion

This chapter analysed the value, veracity, and impact of brokers' output. The most notable conclusion is the consistent and robust tendency for brokers to tilt their recommendations towards firms with positive momentum. The long-term relationship between brokers' recommendations and abnormal returns and volume strongly suggests that brokers are principally followers, rather than leaders, in terms of momentum. Investors could generate greater abnormal returns by simply focusing on small firms with high momentum and B/M ratios than by following analysts' advice.

[131] However, these results are not directly comparable, as Jegadeesh and Kim (2006) and Womack (1996) use daily volume data.

The returns that analysts generate by exploiting momentum and size are reduced by the losses to their B/M and E/P strategies. Analysts tilt their recommendations towards value (growth) stocks in terms of B/M (E/P) ratios. However, such stocks significantly underperform stocks at the opposite end of the valuation spectrum over the six months subsequent to the calendar quarter end.

Recommendation revisions are more informative than recommendation levels and upgrades generate considerably larger abnormal returns than downgrades. This result is largely driven by the economic value contained in the upgrades of Irish brokers. The information content of downgrades is quickly impounded into share prices. Indeed, the negative returns to such revisions reverse in the longer term, implying a market overreaction. In contrast, the returns to upgraded stocks drift in the prescribed direction for a number of months, implying an underreaction to good news. Alternatively, these patterns may be driven by investors' cognisance of the conflicts of interest that analysts face.

Abnormal volume effects are broadly similar for these two revision categories. In stark contrast with prior research, revisions of smaller degrees generate more significant abnormal returns. Further analysis shows that abnormal returns are higher for brokers that follow more firms and for firms that are relatively neglected.

Irish brokers are considerably more optimistic and herd to a greater extent than their international counterparts and their recommendations generate larger abnormal returns. This superior performance is attributable to the performance of upgrades, which exploit momentum in returns. The superior performance of home-based analysts confirms the findings of Bae *et al.* (2008), Orpurt (2002), and Conroy *et al.* (1997). The co-existence of more optimistic and accurate forecasts by Irish brokers may be consistent with the information hypothesis. The finding that Irish brokers produce lower EPS forecasts adds further weight to this possibility, given the dynamics of the earning-guidance game, as outlined in section 4.5.

Chapter Eight

Conclusions

8.1 Introduction

This chapter completes the dissertation and commences by reiterating the objectives of the study in section 8.2. The key findings are summarised and accompanied with a brief discussion of their implications in sections 8.3 and 8.4, respectively. Sections 8.5 and 8.6 outline the contributions and limitations of the research, respectively, while recommendations for future research are provided in section 8.7.

8.2 Objectives

This study aimed to fill a number of apparent gaps in the literature. The overarching objective was to examine the profitability of contrarian and strength rule strategies in four medium-sized European markets, with particular emphasis on the role of brokers. The review of the literature identified a dearth of research on the two anomalies in the four markets in question. Furthermore, the literature on the value and impact of brokers' recommendations is ambiguous and there is limited research relating to the Irish market.

The objectives, as presented in section 1.4, were to answer the following questions:

1. Is it possible to make economically and statistically significant risk-adjusted returns by following strength rule and contrarian strategies in the four markets under review?
2. Is it possible to ameliorate returns by employing alternative rank and holding periods and hybrid strategies?
3. Are apparently abnormal returns more attributable to rational or behavioural factors?
4. Do Irish brokers appear to be more prone to conflicts of interest than their international counterparts?
5. To what extent do brokers follow momentum and contrarian strategies?
6. Do brokers' recommendations have predictive power and what are the volume and price impacts of their output?

These questions were addressed using a quantitative approach. The profitability of the contrarian and strength rule strategies was measured using three asset-pricing models, while the value, veracity, and impact of brokers' output were tested on the Irish market by analysing panel data relating to three forms of projections; EPS forecasts; target prices; and overall recommendation category. A combination of event- and calendar-based strategies was employed in conjunction with a number of models and holding periods. An analysis was also conducted on the firm-specific characteristics of stocks that are favourably recommended by brokers.

8.3 Findings

This section summarises the key findings that emerged from the two principal strands of the research and outlines the implications of these findings for academics, investors, brokers, and regulators. The overarching findings suggest the rejection of the null hypothesis of market efficiency and also call into question whether analysts' recommendations add value.

8.3.1 Anomalies

Chapter six presented the findings pertaining to the momentum and reversal anomalies. The contrarian investment strategy was found to be profitable in three of the four countries. The returns are robust to a number of tests and are particularly consistent in the case of Greece. It is shown that contrarian returns can be enriched via the use of various holding periods, hybrid strategies, and by focusing on extreme stocks.

There is robust evidence that the relatively straightforward strategy of implementing the contrarian investment strategy in year two alone generates consistent and economically significant excess abnormal returns, as it profits from stylised finding of momentum followed by reversal. The returns to such a strategy are particularly striking when portfolios are constructed with extreme stocks.

The role of risk does not appear to be as important as stated in previous research. Although in some cases the use of the CAPM reduces abnormal returns it does not do so to such an extent that it can be cited as a major explanatory variable in the large returns. Furthermore, the abnormal returns cannot be explained by seasonalities, microstructure biases, macroceconomic risk, and short-selling constraints. Moreover, the anomalous evidence is robust to out-of-sample testing, is not attributable to the dynamics of a small number of stocks, and is not limited to a small number of holding periods with disproportionately large abnormal returns.

Ireland is the only country where significant strength rule returns were consistently observed. The optimum strategy involved ranking stocks over nine months and implementing the momentum strategy for approximately two months. The superiority of a relatively short holding period is consistent with the findings of key momentum studies such as Jegadeesh and Titman (1993) and Rouwenhorst (1998). However, the nine-month rank period contrasts with the 12-month period that is found to be optimal in such studies.

The persistent and robust evidence of return continuation leads to a rejection of the null hypothesis of market efficiency in Ireland. It is clear that past performance, especially good performance, is not quickly impounded into share prices. In contrast with key momentum studies, such as Jegadeesh and Titman (1993) and Rouwenhorst (1998), past winners and losers both contribute positively to the strength rule returns. This suggests that the Irish market may underreact to both good and bad news, contradicting the assertion of McQueen *et al.* (1996) that stocks react slowly to good news but quickly to bad news

The significant anomalous returns documented in chapter six may suggest that the actions of noise traders have a material impact on share prices. Paradoxically, the efforts of individual countries and the European Union (Short Selling) Regulations 2012 (236/20012), which aim to co-ordinate efforts to tackle the potentially de-stabilising effects of short selling, may increase the limits to arbitrage, and concomitantly, the noise component in stocks prices.

There is evidence of systematic seasonalities in returns. However, such seasonal patterns tend to affect the winner and loser portfolios to a similar extent. Accordingly, they do not permeate to the level of excess abnormal returns and one can conclude that seasonalities cannot account for the anomalous evidence documented in this thesis. The returns to both strategies tend to be more significant during bear markets. Contrarian returns are higher following market upturns, while there is no relationship between momentum returns and lagged market returns.

There is mixed evidence relating to the validity of behavioural explanations for continuation followed by reversal. The finding that momentum profits are not positively correlated with lagged market returns runs counter to the predictions of models relating to overconfidence and loss aversion. However, the positive relationship between contrarian returns and lagged momentum returns suggests that the two anomalies are related phenomena and reversals may be the consequence of the unwinding of previous overreactions.

In summary, the anomalous returns documented in this thesis cannot be accounted for by rational explanations such as risk, seasonalities, short-selling constraints, firm size, and macroeconomic risk. Furthermore, abnormal returns are not driven by the dynamics of a small number of stocks or holding periods and are robust to out-of-sample testing.

8.3.2 Brokers' recommendations

Chapter seven analysed the value, veracity, and impact of brokers' output. The most robust finding is brokers' tendency to tilt their recommendations towards small firms with positive price momentum. The evidence adduced relating to abnormal returns and volume suggests that brokers are principally followers of, rather than contributors to, return continuation.

Brokers' recommendations and forecasts do not provide a basis for generating abnormal returns above the level attainable by exploiting relatively easily observable variables such as past momentum and firm size. This is largely the result of brokers incorrectly tilting their recommendations towards value (growth) stocks in terms of B/M (E/P) ratios. Irish brokers are more optimistic and exhibit a greater tendency to herd and follow momentum strategies than international brokers.

Consistent with existing research (for example, Jegadeesh and Kim, 2006; Brav and Lehavy, 2003), revisions provide a superior basis for investment than recommendation levels. Upgrades generate considerably larger abnormal returns than downgrades but the abnormal volume effects are broadly similar for both revision categories. In stark contrast with prior research, revisions of smaller degrees generate more significant abnormal returns.

The asymmetric market reaction to upgrades and downgrades suggests that investors underreact to good news and overreact to bad news. This is consistent with the findings presented in chapter six, where the majority of the momentum and contrarian returns were generated by past winners and losers, respectively. This suggests that the anomalous returns are principally attributable to underreaction to good news and overreaction to bad news, respectively.

Alternatively, the divergent responses are driven by conflicts of interest, as investors downgrade the recommendations of analysts, thereby delaying (accelerating) the market response to upgrades (downgrades). Brokers react in a similar fashion to other investors, as they downgrade poor performing stocks rapidly but respond in a more delayed fashion to stocks with positive return momentum.

8.4 Implications

The above findings have a number of implications for academics, investors, brokers, and regulators. The implications for investors relate to the trading strategies examined in chapter six and the findings pertaining to brokers discussed in chapter seven. Investors in the Irish market could profit from momentum trading strategies. Return continuation appears to be a short- to medium-term phenomenon and investors can maximise average monthly returns by employing nine-month rank and seven-week holding periods. Furthermore, momentum returns can be increased by skipping a week between the portfolio rank and holding periods.

Contrarian investment strategies dominate in the other three markets and the Greek market appears to offer the most fertile ground for profiting from return reversals. Furthermore, investors are advised to form winner and loser portfolios using stocks with extreme past returns. A relatively straightforward strategy of implementing a contrarian investment strategy in year two alone represents a potentially profitable approach with the added benefit of reduced transaction costs relative to three-year holding periods. Hybrid strategies that combine the two strategies in recognition of their differing holding periods are capable of successfully exploiting continuation followed by reversal.

Recall that both strategies generated particularly elevated abnormal returns during economic downturns. This may not be of practical investment value as it is difficult to predict market or economic growth rates. In contrast, the finding that contrarian returns tend to be more significant *following* market upturns does present an *ex ante* implementable strategy.

The second set of implications pertaining to investors relates to the value of brokers' output. It is questionable whether the funds expended on the research conducted by financial analysts represent a worthwhile undertaking or whether it constitutes an economic loss, which is largely funded by investors through fees. Investors could generate greater abnormal returns by simply focusing on small firms with high momentum and B/M ratios than by following analysts' advice. If investors are to follow brokers, it is prudent to focus on revisions. The returns to upgrades are more significant and the window of opportunity is not as restrictively narrow as is the case for downgrades due to the asymmetric market response to good and bad news documented in both strands of the research.

There are four significant implications for academics. First, the use of non-overlapping returns can provide a clearer insight the value of brokers' recommendations by eliminating cross-sectional dependence. Second, focussing on target prices, rather than recommendation levels, provides greater scope for differentiating between the strength of analysts' output.

Third, it is important to test the robustness of any apparently anomalous returns by employing a number of models and out-of-sample testing periods. Finally, studies of contrarian returns should utilise alternative rank and holding periods, as the standard three-year rank and holding periods are typically sub-optimal. The abnormal returns to six-month rank periods are particularly elevated and merit further examination.

Brokers should continue to tilt their recommendations towards small stocks with positive price momentum. However, it would appear that a reversal of their strategy vis-à-vis book-to-market and earnings-to-price ratios may be judicious. Brokers could also benefit from following more stocks, particularly those that are relatively neglected[132]. This study lends further weight to the assertion of Carhart (1997) that brokers and fund managers should not be rewarded for exploiting momentum and size, as such variables are easily observable.

The findings of this research also have a number of potential implications for regulators. If optimism is a proxy for conflicts of interest then it would appear that Irish analysts are considerably more conflicted than their international counterparts. Analysts may be cheerleaders for the firms that they follow, as argued by Chan *et al.* (2007), rather than impartial observers whose advice should be taken at face value.

8.5 Contribution

This study makes a number of important contributions to the literature pertaining to the continuation and reversal anomalies. Above all, it fills an important research gap by analysing four markets that have largely been neglected in the existing literature. The results provide out-of-sample confirmation of the findings relating to more widely scrutinised markets.

The study also adopts a number of novel methodological approaches and unearths some findings that contradict existing research. For example, the use of hybrid strategies,

[132] This implication is with the goal of improving forecast accuracy in mind; it ignores any other motivations such as those relating to underwriting fees, commissions, access to information, etc.

alternative rank periods, and cross-product ratios and the significant contrarian returns to six-month rank periods contribute to the understanding of share price dynamics.

The inclusion of data incorporating the global financial crisis facilitates a more complete analysis of the relationship between anomalous returns and market states. The use of a small stock portfolio and non-overlapping returns reduces microstructure bias and cross-sectional dependence problems. Furthermore, the use of expected price change as a percentage of current price, instead of recommendation levels, allows for analysts' views to be examined on a continual scale. Finally, the analysis of an oligopolistic market for investment advice illuminates the importance of conflicts of interest and may be of interest to regulators.

8.6 Limitations

The conclusions from this research should be interpreted within the context of a number of limitations. This study relies exclusively on a quantitative approach. While this facilitated a broad dataset across temporal and cross-sectional dimensions, it comes at the loss of the greater detail that accompanies a qualitative approach.

Given the nature of the markets analysed, the sample size and time period employed were limited relative to those used in much of the existing literature that focusses on larger stock markets. This study does not explicitly account for transaction costs. Returns are only considered significant if they exceed a reasonably high threshold suggested by existing research into trading costs. However, it is likely that such costs are higher in the small markets used in this study.

Although a suite of models was employed, statistical inferences must be interpreted with caution in light of the joint-hypothesis problem. As outlined in section 5.3.1, Fama-French factors are not available on an individual basis for the four markets under review. The lack of such factors is overcome to some degree by including size, B/M, and E/P in the quintile approach in conjunction with brokers' recommendations. However, this does not constitute a perfect substitute for the robustness that would be gained by employing the Fama-French three-factor or Carhart four-factor models.

Although there is no *systematic* survivorship bias, as outlined in section 5.2, there is a possible bias introduced as some firms had to be excluded from the analysis pertaining to brokers' recommendations due to missing historic accounting data.

The out-of-sample period (2007-09) coincided with the global financial crisis. While this facilitated a comparison between the returns to the two anomalies in differing economic states, the period is far from representative. The impact of the acute market downturn is particularly germane in the analysis of brokers' forecasts as it manifests itself in exaggerated *ex post* analyst optimism.

8.7 Recommendations for future research

The findings of this thesis initiate a number of suggestions for the trajectory of future research. It would be valuable to re-examine the findings of this research using a larger sample over an extended time period. It would also be enlightening to test whether the results generalise to other markets or are specific to the four markets under review.

The high excess abnormal returns to the contrarian strategy using six-month rank periods contrasts starkly with the findings in the literature and merits further examination. It would also be interesting to examine the profitability contrarian strategies in the second holding period year in other markets. It would also be illuminating to examine whether the asymmetric response to the news contained in past returns and analysts' revisions is also present in the case of earnings announcements, thereby leading to PEAD.

Future research could also investigate the link between brokers' output and commissions and investment banking fees in order to illuminate the conflicts of interest that analysts face. Furthermore, interviews with brokers may complement the insights gained from the cross-sectional analysis undertaken in this research by facilitating a greater understanding of the motives and strategies pertaining to these pivotal players in the financial market.

It may take a number of years for the nascent regulatory efforts at tackling conflicts of interest to manifest themselves in a pronounced change in analyst behaviour; this provides a potentially fruitful area for future research.

Recall that the forecasts of Irish brokers were simultaneously more optimistic and more accurate than their international counterparts. It would be instructive to examine whether this superior performance is attributable to an informational advantage that may stem from a closer relationship with covered firms. An analysis of the trading activities of brokerage firms and investment houses would also be potentially informative to this end.

The creation of a dataset of Fama-French factors for individual markets would represent a meritorious exercise. Such an undertaking is proving to be a fruitful endeavour for the UK market and it would ameliorate research in smaller markets in many areas of financial analysis.

Although seasonalities could not account for the anomalous returns documented in this study, there were a number of robust seasonal patterns in returns that merit closer examination. The observed positive returns in April and May and negative returns in September in all four markets possibly represent the most interesting grounds for future research. In addition, the finding that returns are negative in Norway in September and October in 17 of the 20 years demands further investigation.

The finding that the largest anomalous returns were observed in the countries that subsequently experienced the most significant stock market crashes as a result of the global financial crisis suggests that research should continue to investigate the link between overreaction and bubbles.

Thaler's (1999) claim that the term 'behavioural finance' would soon become redundant has proven somewhat premature. However, although the search for a unifying model of investor sentiment may be quixotic, future research should continue to focus on developing behavioural models that incorporate investor sentiment and cognitive errors. Qualitative studies that aim to further understand the cognitive forces that motivate investors would thus represent a valuable path for future research.

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Appendix A

Markets studied in multi-country momentum studies

Balvers and Wu (2006)	Australia, Austria, Belgium, Canada, Denmark, France, Germany, Hong Kong, Italy, Japan, Netherlands, Norway, Singapore, Spain, Sweden, Switzerland, UK, US.
Bhojraj and Swaminathan (2006)	Argentina, Australia, Austria, Belgium, Brazil, Canada, Chile, Denmark, Finland, France, Germany, Greece, Hong Kong, Indonesia, Ireland, Italy, Japan, Korea, Malaysia, Mexico, Morocco, Netherlands, New Zealand, Norway, Philippines, Poland, Portugal, Singapore, South Africa, Spain, Sweden, Switzerland, Taiwan, Thailand, Turkey, UK, US, Venezuela.
Bird and Whitaker (2003)	France, Germany, Italy, The Netherlands, Spain, Switzerland, UK.
Brown *et al.* (2008)	Hong Kong, Korea, Singapore, Taiwan.
Doukas and McKnight (2005)	Austria, Belgium, Denmark, Finland, France, Germany, Italy, Netherlands, Norway, Spain, Sweden, Switzerland, UK.
Du (2008)	Australia, Austria, Belgium, Canada, Denmark, France, Germany, Hong Kong, Italy, Japan, the Netherlands, Norway, Singapore, Spain, Sweden, Switzerland, UK, US.
Fong *et al*. (2004)	Australia, Austria, Belgium, Canada, Denmark, France, Germany, Hong Kong, Indonesia, Italy, Japan, Korea, Malaysia, Netherlands, Norway, Singapore, South Africa, Spain, Sweden, Switzerland, Taiwan, Thailand, UK, US.
Griffin *et al*. (2005)	Argentina, Australia, Austria, Belgium, Brazil, Canada, Chile, China, Denmark, Egypt, Finland, France, Germany, Greece, Hong Kong, India, Indonesia, Ireland, Italy, Japan, Malaysia, Mexico, Netherlands, New Zealand, Norway, Pakistan, Peru, Philippines, Portugal, Singapore, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, Turkey, UK, US.
Hameed and Kusnadi (2002)	Hong Kong, Malaysia, Singapore, South Korea, Taiwan, and Thailand.
Huang (2006)	Australia, Austria, Belgium, Denmark, France, Germany, Hong Kong, Italy, Japan, Netherlands, Norway, Singapore, Spain, Sweden, Switzerland, the UK and the US.

Liu *et al*. (2011)	Australia, Austria, Belgium, Canada, Denmark, France, Germany, Hong Kong, Italy, Japan, the Netherlands, Norway, Russia, Singapore, South Korea, Spain, Sweden, Switzerland, Taiwan, UK.
Muga and Santamaria (2007b)	Argentina, Brazil, Chile, Mexico.
Naranjo and Porter (2007)	**Developed:** Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Italy, Japan, Luxembourg, Netherlands, New Zealand, Norway, Singapore, Spain, Sweden, Switzerland, UK, USA. **Emerging:** Argentina, Brazil, Chile, Greece, India, Indonesia, Israel, Korea, Malaysia, Mexico, Philippines, Poland, Portugal, Russia, South Africa, Taiwan, Thailand, Turkey.
Nijman *et al*. (2004)	Italy, Denmark, Ireland, France, Sweden, Finland, UK, Spain, Switzerland, Netherlands, Norway, Germany, Portugal, Belgium, Austria.
Pan and Hsueh (2007)	Austria, Belgium, Denmark, France, Germany, Italy, The Netherlands, Norway, Spain, Sweden, Switzerland, UK, US.
Patro and Wu (2004)	Australia, Austria, Belgium, Canada, Denmark, France, Germany, Hong Kong, Italy, Japan, Netherlands, Norway, Singapore, Spain, Sweden, Switzerland, UK.
Rouwenhorst (1998)	Austria, Belgium, Denmark, France, Germany, Italy, Norway, Spain, Sweden, Switzerland, Netherlands, UK.
Rouwenhorst (1999)	Argentina, Brazil, Chile, Columbia, Greece, Indonesia, India, Jordan, Korea, Malaysia, Mexico, Nigeria, Pakistan, Philippines, Portugal, Taiwan, Thailand, Turkey, Venezuela, Zimbabwe.
Ryan and Curtin (2006)	India, Indonesia, Hong Kong, Malaysia, Singapore, South Korea, and Taiwan
Shen *et al*. (2005)	**Developed:** Australia, Austria, Belgium, Canada, France, Germany, Hong Kong, Italy, Japan, Netherlands, Norway, Singapore, Spain, Sweden, Switzerland, UK, US. **Emerging:** Argentina, Brazil, Chile, Greece, Indonesia, Korea, Malaysia,

	Mexico, The Philippines, Portugal, Taiwan, Thailand, and Turkey.
Van der Hart *et al.* (2003)	China, India, Indonesia, Korea, Malaysia, Pakistan, Philippines, Sri Lanka, Taiwan, Thailand, Czech Republic, Egypt, Greece, Hungary, Israel, Jordan, Morocco, Nigeria, Poland, Portugal, Russia, Slovakia, South Africa, Turkey Zimbabwe, Argentina, Brazil, Chile, Colombia, Mexico, Peru, and Venezuela.
Van Dijk and Huibers (2002)	Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the UK.

Appendix B

Markets studied in multi-country reversal studies

Balvers *et al.* (2000); Balvers and Wu (2006)	Australia, Austria, Belgium, Canada, Denmark, France, Germany, Hong Kong, Italy, Japan, Netherlands, Norway, Singapore, Spain, Sweden, Switzerland, UK, US.
Bird and Whitaker (2003)	France, Germany, Italy, Netherlands, Spain, Switzerland, UK.
Barros and Haas (2008)	Brazil, Chile, Czech Republic, Hungary, Indonesia, Malaysia, Mexico, Pakistan, Philippines, Poland, Romania, South Africa, Singapore, Thailand, Turkey.
Bauman *et al.* (1999)	Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Italy, Japan, Malaysia, Netherlands, New Zealand, Norway, Singapore, Spain, Sweden, Switzerland, UK.
Baytas and Cakici (1999)	France, UK, Germany, Italy, Canada, Japan
Brouwer *et al.*(1997)	France, Germany, Netherlands, UK.
Haugen and Baker (1996)	France, Germany, Japan, UK, US.
Jordan (2012)	**Main Dataset (1924-2005):** Australia, France, Germany, Italy, Japan, Sweden, UK, US. **Secondary Dataset (1969-2005):** Austria, Canada, Denmark, Finland, Hong Kong, the Netherlands, Spain, and Switzerland.
Larson and Madura (2001)	**Emerging currency markets:** Hong Kong, Israel, Malaysia, Singapore, South Korea. **Industrial currency markets:** Belgium, Britain, Canada, France, Germany, Italy, Japan, Spain, Sweden, Switzerland.
McInish *et al.* (2008)	Japan, Taiwan, Korea, Hong Kong, Malaysia, Thailand, and Singapore.
Richards (1997)	Australia, Austria, Canada, Denmark, France, Germany, Hong Kong, Italy, Japan, the Netherlands, Norway, Spain, Sweden, Switzerland, the UK, US.
Schaub *et al*. (2008)	Korea, Hong Kong, Japan.

Appendix C

Details of key broker studies

Author(s)	Market(s)	Sample size
Elton *et al.* (1986)	US	9,977 recommendations (1,156 changes)
Stickel (1995)	US	16,957 buy and sell recommendations (21,387 changes)
Womack (1996)	US	1,573 changes
Ho and Harris (1998)	US	4,436 revisions
De Bondt and Forbes (1999)	UK	168,307 EPS forecasts
Desai *et al.* (2000)	US	1,158 buy recommendations
Aitken *et al.* (2000)	Australia	115,720 recommendations
Jegadeesh *et al.* (2004)	US	54,400 recommendations
Bernhardt *et al*. (2006)	US	387,756 observations
Jegadeesh and Kim (2006)	US, UK, Canada, France, Germany, Italy, Japan	172,125 firm-years (191,174 changes)
Moshirian *et al.* (2009)	Argentina, Brazil, China, Chile, Hungary, India, Indonesia, Israel, Korea, Mexico, South Africa.	111,770 revisions

Appendix D

Analyst coverage by firm

The table details brokers' output by company. The last column presents the number of analysts following each firm.

Company	Price Forecasts	%	EPS Forecasts	%	Recommendations	%	# Analysts Following
AIB	5,724	12.47	1583	9.56	8,887	12.55	34
BOI	5,222	11.37	1086	6.56	8,519	12.03	32
Ryanair	5,194	11.31	1550	9.36	8,031	11.34	29
CRH	4,479	9.75	1272	7.68	8,478	11.98	25
Paddy Power	2,707	5.90	941	5.68	3,675	5.19	21
IL&P	2,178	4.74	583	3.52	1,419	2.00	7
Elan	2,130	4.64	568	3.43	3,153	4.45	20
C&C	2,124	4.63	1127	6.81	2,459	3.47	17
Kingspan	1,653	3.60	749	4.52	2,400	3.39	13
Grafton	1,591	3.46	297	1.79	2,319	3.28	9
Icon	1,591	3.46	683	4.12	1,916	2.71	10
Greencore	1,242	2.70	896	5.41	2,514	3.55	9
Independent	1,216	2.65	426	2.57	3,350	4.73	8
DCC	947	2.06	258	1.56	1,420	2.01	6
McInerney	930	2.03	386	2.33	1,299	1.83	6
Aryzta	898	1.96	495	2.99	1,540	2.18	10
United Drug	863	1.88	348	2.10	1,364	1.93	8
Smurfit	767	1.67	587	3.54	823	1.16	11
Kerry	667	1.45	336	2.03	1,284	1.81	6
IFG	658	1.43	238	1.44	893	1.26	5
Dragon Oil	639	1.39	237	1.43	708	1.00	8
Glanbia	631	1.37	443	2.68	1,538	2.17	5
Abbey	605	1.32	536	3.24	1,298	1.83	5
FBD	586	1.28	200	1.21	700	0.99	3
CPL	383	0.83	364	2.20	448	0.63	3
Aer Lingus	293	0.64	371	2.24	359	0.51	4
Total	**45,918**	**100**	**16,560**	**100**	**70,794**	**100**	

Appendix E

Coverage by broker

The table presents the percentage share of output by broker. Any stock with less than 1% of the output in all three categories is amalgamated into the 'other' category.

Broker	**Recommendations (%)**	**Price Forecasts (%)**	**EPS Forecasts (%)**
NCB Stockbrokers	11.43	11.50	9.42
Goodbody Stockbrokers	11.04	13.25	17.60
Merrion Stockbrokers	7.26	4.35	10.17
Citi	5.93	4.93	0.90
ABN AMRO Global Research	5.42	4.13	3.73
Goldman Sachs Research	5.04	4.05	5.35
BAS-ML	4.33	3.05	2.54
UBS Equities	3.74	4.65	5.90
Deutsche Bank Research	3.54	3.80	4.30
Credit Suisse	3.32	3.65	3.19
Dresdner Kleinwort	3.10	3.75	2.72
Morgan Stanley	2.81	3.09	1.13
J.P.Morgan Securities Equities	2.46	1.73	2.24
Lehman Brothers Equity Research	1.91	2.10	1.75
Societe Generale	1.76	2.20	1.18
HSBC	1.72	0.09	0.38
Exane BNP Paribas	1.40	2.16	2.67
Investec Securities (UK)	1.31	0.57	1.44
Keefe, Bruyette & Woods, Inc.	1.28	1.98	1.97
IIR Group	1.21	1.88	0.30
Commerzbank Corporates & Markets	1.13	0.67	0.00
ING FM	1.11	0.25	0.53
WestLB Equity Markets	0.92	1.30	0.17
Evolution Securities Ltd	0.76	1.18	0.30
Oddo Securities	0.75	1.09	0.58
DZ Bank	0.43	0.56	1.32
Collins Stewart & Co	0.39	0.52	1.45
Davy	0.00	6.20	11.35
Others	14.51	11.33	5.41
Total	**100**	**100**	**100**

Appendix F

Buy-to-sell ratios in existing literature

Author	**Country**	**Buy-to-sell ratio**
Lloyd-Davies and Canes (1978)	US	3.2:1
Elton *et al.* (1986)	US	3.5:1
Stickel (1995)	US	4.6:1
Ho and Harris (1998)	US	5.2:1
Womack (1996)	US	7:1
Rajan and Servaes (1997)	US	
Aitken *et al.* (2000)	Australia	3.25*
Jegadeesh *et al.* (2004)	US	18.8:1
	Britain	3.9:1
	Canada	4.8:1
	France	3.3:1
	Germany	1.9:1
	Italy	2.8:1
	Japan	2.5:1
Michaely and Womack (2004)		
Jegadeesh and Kim (2006)	US	3.6:1
Ryan (2006)	Ireland	7.2:1
Moshirian *et al.* (2009)	Emerging markets	1.4:1*

* denotes a ratio of positive-to-negative recommendations.

Appendix G

Revisions by market in existing studies

The table presents the number of upgrades and downgrades on a market-by-market basis as detailed Jegadeesh and Kim (2006) and Moshirian *et al.* (2009). For ease of comparison with the results of this study, the percentage of upgrades and downgrades is calculated for each market.

Jegadeesh and Kim (2006)

Market	**Upgrades**	**Downgrades**	**Up %**	**Down %**
US	50,238	63,444	44.19%	55.81%
Britain	10,930	11,063	49.70%	50.30%
Canada	9,667	10,498	47.94%	52.06%
France	6,510	6,898	48.55%	51.45%
Germany	5,252	5,713	47.90%	52.10%
Italy	1,847	1,947	48.68%	51.32%
Japan	3,522	3,645	49.14%	50.86%
All	87,966	103,208	46.01%	53.99%
Non-US	37,728	39,764	48.69%	51.31%

Moshirian *et al.* (2009)

Market	**Upgrades**	**Downgrades**	**Up %**	**Down %**
Argentina	1,859	1,864	49.93%	50.07%
Brazil	7,965	6,217	56.16%	43.84%
China	6,826	5,775	54.17%	45.83%
Chile	1,189	1,148	50.88%	49.12%
Hungary	961	919	51.12%	48.88%
India	4,976	4,974	50.01%	49.99%
Indonesia	646	686	48.50%	51.50%
Israel	166	154	51.88%	48.13%
Korea	21,313	19,547	52.16%	47.84%
Mexico	2,747	2,622	51.16%	48.84%
South Africa	10,158	9,058	52.86%	47.14%
Total	58,806	52,964	52.61%	47.39%

Appendix H

Summary statistics on firm-specific attributes

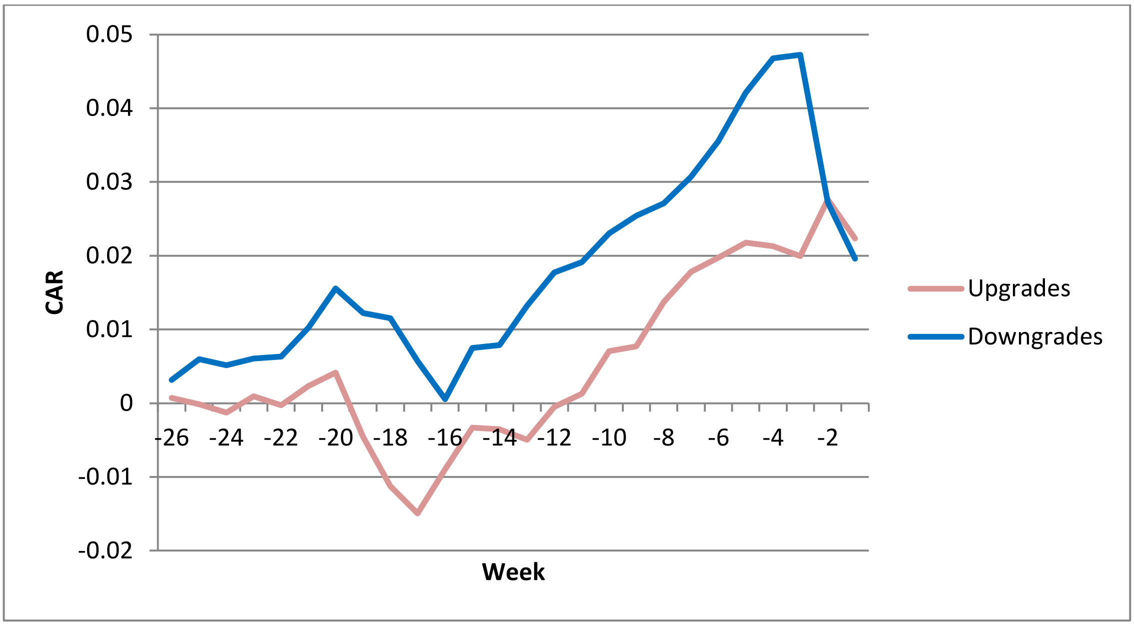
The table presents summary statistics on the value of each firm-specific variable and the number of firms for which data is available in each quarter.

	Value		Number of firms	
Variable	**Mean**	**Median**	**Mean**	**Median**
Rating	4.01	4.00	23	23
6 month returns	0.04	0.01	24	24
3 month returns	0.02	0.00	24	24
Volume	1.16	1.04	24	24
Size	20.81	20.78	22	21
Book-market	0.61	0.41	21	21
Expected price change	31.09	13.50	22	24
Rating change	-0.01	0.00	21	22
Change in expected price change	0.96	-0.02	22	23
Future 3 month return	0.02	0.00	24	24
Future 6 month return	0.05	0.01	24	24
Dispersion	0.14	0.09	21	22
Future Volume	1.21	1.06	24	24
Earnings/Price	15.04	12.95	19	20

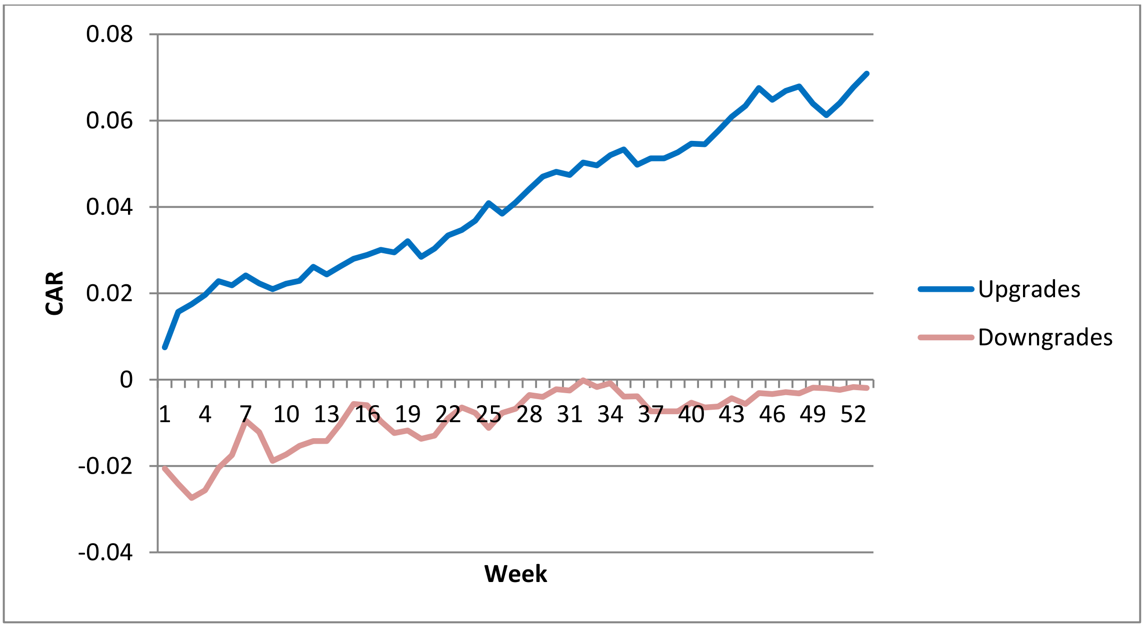
Appendix I

Pre- and post-revision abnormal returns

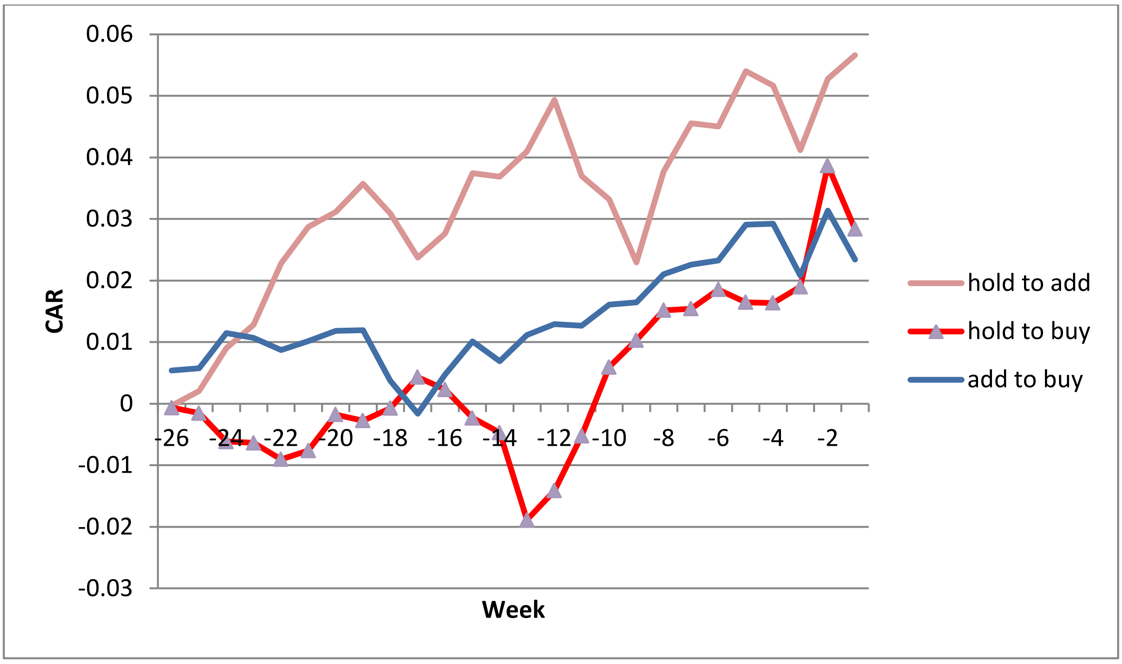
Pre-revision abnormal returns to upgrades and downgrades



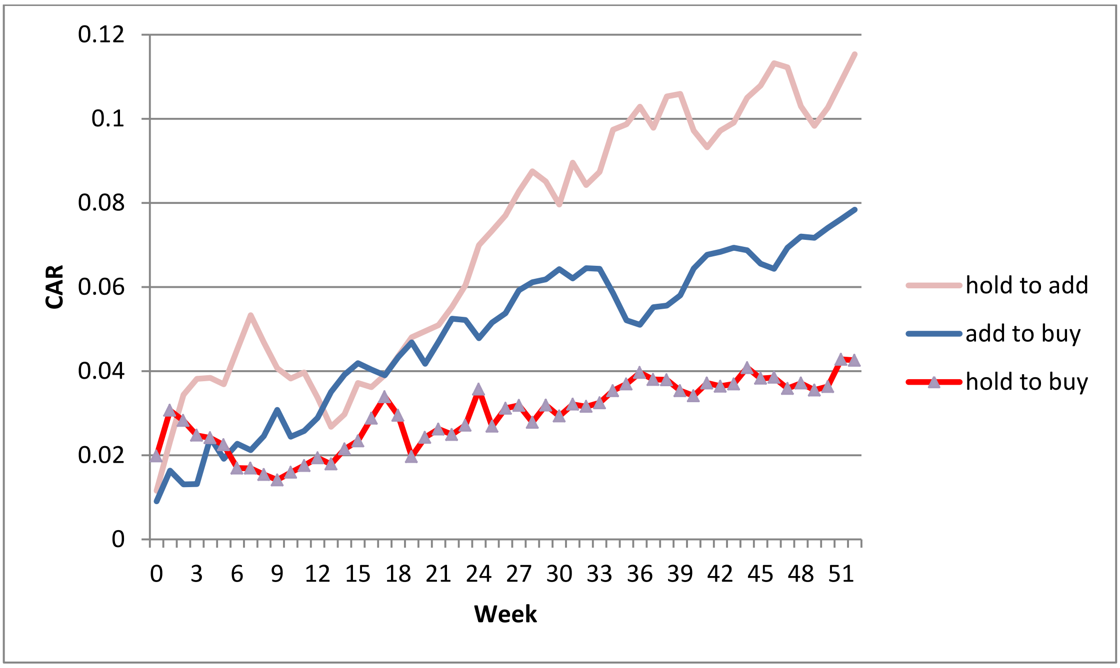
Post-revision abnormal returns to upgrades and downgrades



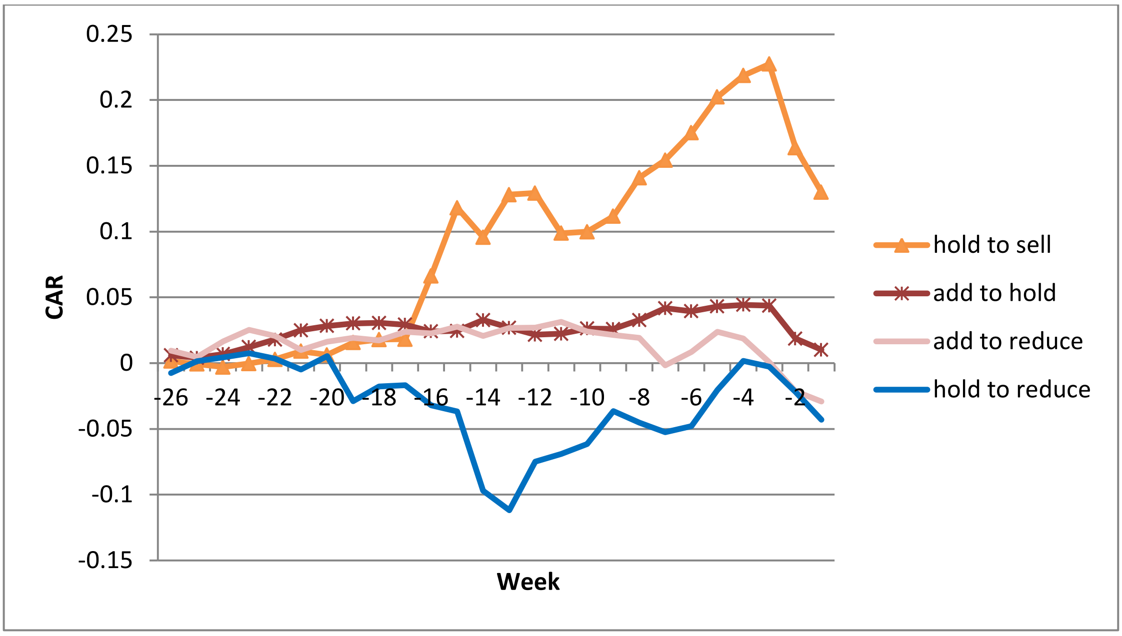
Pre-revision abnormal returns to key upgrades



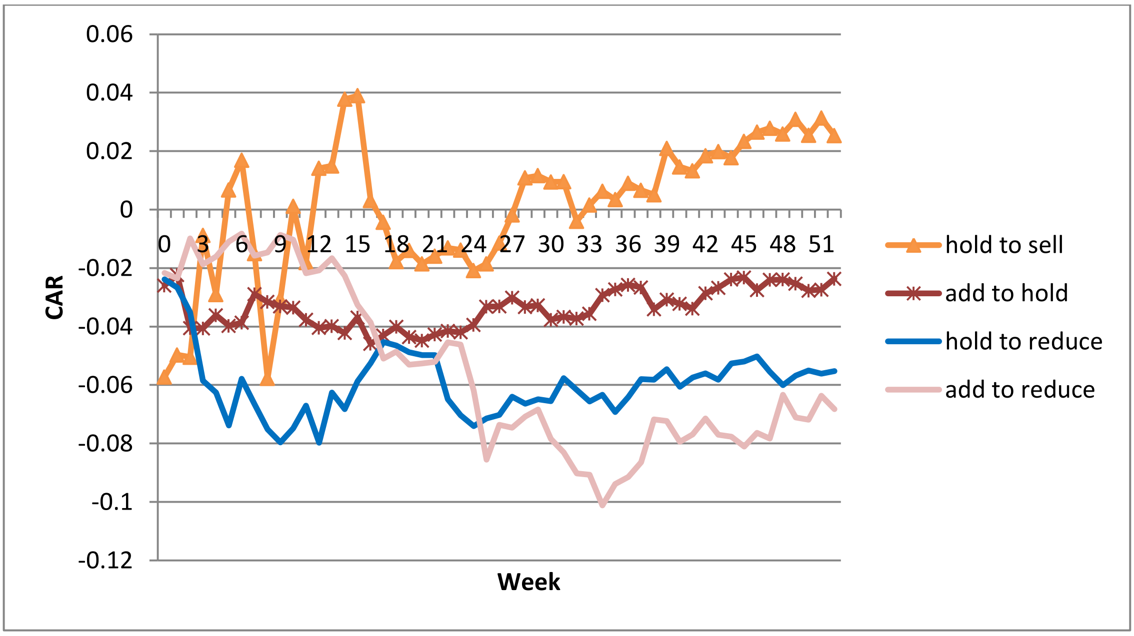
Post-revision abnormal returns to key upgrades



Pre-revision abnormal returns to key downgrades



Post-revision abnormal returns to key downgrades



Appendix J

Standardised volume

The table presents the standardised volume for each revision category from week -2 to +2. Standardised volume is insignificant for all categories outside of this window. One-sided statistical significance at the 1, 5, and 10% level is indicated by *, **, and *** respectively.

Revision category	Week relative to revision				
	-2	**-1**	**0**	**1**	**2**
add to buy	1.11	1.05	1.32*	1.37*	1.16
add to hold	1.13***	1.11	1.39*	1.15	1.02
add to reduce	1.21	1.17	1.22	0.92	1.27
add to sell	1.04	0.67	0.75	1.07	1.01
buy to add	0.91	1.21	1.33*	1.24*	1.11***
buy to hold	1.02	1.11	1.22*	1.09	1.12
buy to reduce	1.02	1.13	1.80	1.80*	1.25
buy to sell	0.96	1.06	1.13	1.08	0.75
hold to add	0.91	1.02	1.49*	1.00	0.96
hold to buy	0.96	1.13	1.20*	0.97	0.96
hold to reduce	0.87	1.32*	1.48*	1.22**	1.11
hold to sell	0.94	1.14	1.42*	1.20	1.30
reduce to add	1.25	1.91	1.24**	1.44	1.02
reduce to buy	0.82	0.95	1.18	0.85	0.92
reduce to hold	1.06	0.91	1.32*	0.88	1.01
reduce to sell	0.83	0.87	1.22	3.03	1.35
sell to add	1.55	1.37	1.18	1.64	0.57
sell to buy	0.90	1.06	1.35	1.31	1.07
sell to hold	0.95	1.33	1.38**	1.06	1.01
sell to reduce	0.80	2.21	1.46	1.03	0.64
Upgrades	1.01	1.13*	1.31*	1.12**	1.03
Downgrades	1.00	1.15*	1.32*	1.20*	1.12*