

Representative Agent Earnings Momentum Models: The
Impact of Sequences of Earnings Surprises on Stock
Market Returns under the Influence of the Law of Small
Numbers and the Gambler's Fallacy

by

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Dedication

“Blessing and honour and glory and power be to Him who sits on the throne, and to the Lamb, forever and ever!”

– Revelation 5:13

Abstract

This thesis examines the response of a representative agent investor to sequences (streaks) of quarterly earnings surprises over a period of twelve quarters using the United States S&P500 constituent companies' sample frame in the years 1991 to 2006. This examination follows the predictive performance of the representative agent model of Rabin (2002b) – [Inference by believers in the law of small numbers. *The Quarterly Journal of Economics*. 117(3).p.775 – 816] and Barberis, Shleifer, and Vishny (1998) – [A model of investor sentiment. *Journal of Financial Economics*. 49. p.307 – 343] for an investor who might be under the influence of the law of small numbers, or another closely related cognitive bias known as the gambler's fallacy. Chapters 4 and 5 present two related empirical studies on this broad theme.

In chapter 4, for successive sequences of annualised quarterly earnings changes over a twelve-quarter horizon of quarterly earnings increases or falls, I ask whether the models can capture the likelihood of reversion. Secondly, I ask, what is the representative investor's response to observed sequences of quarterly earnings changes for my S&P500 constituent sample companies? I find a far greater frequency of extreme persistent quarterly earnings rises (of nine quarters and more) than falls and hence a more muted reaction to their occurrence from the market. Extreme cases of persistent quarterly earnings falls are far less common than extreme rises and are more salient in their impact on stock prices. I find evidence suggesting that information discreteness; that is the frequency with which small information about stock value filters into the market is one of the factors that foment earnings momentum in stocks. However, information discreteness does not subsume the impact of sequences of annualised quarterly earnings changes, or earnings "streakiness" as a strong candidate that drives earnings momentum in stock returns in my S&P500 constituent stock sample. Therefore, earnings streakiness and informational discreteness appear to have separate and additive effects in driving momentum in stock price.

In chapter 5, the case for the informativeness of the streaks of earnings surprises is further strengthened. This is done by examining the explanatory power of streaks of earnings surprises in a shorter horizon of three days around the period when the effect of the nature of earnings news is most intense in the stock market. Even in shorter windows, investors in S&P500 companies seem to be influenced by the lengthening of negative and positive streaks of earnings surprises over the twelve quarters of quarterly earnings announcement I study here. This further supports my thesis that investors underreact to sequences of changes in their expectations about stock returns. This impact is further strengthened by high information uncertainties in streaks of positive earnings surprise. However, earnings 'streakiness' is one discrete and separable element in the resolution of uncertainty around

equity value for S&P 500 constituent companies. Most of the proxies for earnings surprise show this behaviour especially when market capitalisation, age and cash flow act as proxies of information uncertainty. The influence of the gambler's fallacy on the representative investor in the presence of information uncertainty becomes more pronounced when I examine increasing lengths of streaks of earnings surprises. The presence of post earnings announcement drift in my large capitalised S&P500 constituents sample firms confirms earnings momentum to be a pervasive phenomenon which cuts across different tiers of the stock markets including highly liquid stocks, followed by many analysts, which most large funds would hold.

Keywords: earnings momentum, earnings momentum models, representative agent, streak of earnings surprise, sequence of quarterly earnings change, information uncertainty, gambler's fallacy, law of small numbers, standardised unexpected earning, underreaction.

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List of abbreviations

ABR	Abnormal returns
ACOV	Analysts coverage
AFORD	Analysts forecast dispersion
AFORR	Analysts forecast revisions
BHAR	Buy-and-Hold Abnormal Returns
BSV	Barberis, Shleifer, and Vishny
BTMR	Book-to-market ratio
CAR	Cumulative Abnormal Returns
CEO	Chief executive officer
CVOL	Cash-flow volatility
DHS	Daniel, Hirshleifer, and Subrahmanyam
EMH	Efficient Market Hypothesis
EPS	Earnings-per-share
ESURP	Earnings Surprise
GAAP	Generally Accepted Accounting Principles
GICS	Global Industry Classification Standard
HIU	High information uncertainty
HML	High minus low
HS	Hong and Stein
LIU	Low information uncertainty
I/B/E/S	Institutional Brokers' Estimate System
MBHAR	Mean buy-and-hold abnormal returns
MCAP	Market capitalisation
MRET	Momentum returns
NYSE	New York Stock Exchange
OLS	Ordinary least squares
PEAD	Post earnings announcement drift
S&P500	Standard and Poor 500 index
SUE	Standardised unexpected earnings
SVOL	Stock returns volatility
WML	Winners minus losers

PMN	Positive minus negative
PRET	Cumulative returns over past 12 months
REIT	Real estate investment trust
VAR	Value at risk

Chapter 1

Introduction

1.1 Market efficiency and investor behaviour: neoclassical economics assumptions

The neoclassical economics school of thought makes various assumptions about the efficiency of capital markets and how rational investors behave in these markets. This school of thought applies the concept of rational expectations in the pricing of risky assets. It requires that rational investors must meet a certain number of conditions when making decisions under uncertainty. Such individuals must meet a minimum set of conditions for rational decision-making, as set out by von Neumann-Morgenstern's axioms of cardinal utility. Both concepts of rational expectations and axioms of cardinal utility are based on the belief in the standard economic assumption that people will behave in certain ways that maximise their utility or profits.

The theory of rational expectations was mainly developed in the works of Muth (1960, 1961). In both works, Muth posits that it is difficult to obtain accurate information for the future outcomes of any random event. His theory further extends the description of various economic situations where outcomes usually depend on people's expectations. A good example is the fact that current prices of securities depend partly on what buyers and sellers believe their value will be in the future. This belief may lead to a rush to buy or sell a certain stock, and this behaviour may cause the stock to either appreciate or depreciate in market value. In order to form expectations, people try to forecast what future outcomes such as the price of a security will be. The rational expectations theory reasons that outcomes do not depart systematically from their expected values. However, the theory implies that people could make forecasting errors, but the errors will not persistently occur on a particular side – forecasting errors over time are expected to be random in nature. According to Forsythe *et al* (1982), the rational expectation hypothesis predicts that the price of a security embodies the entire expected stream of future payoffs, and this includes the future value of the security when it is sold to another party. The implication of the rational expectation theory therefore is that capital markets are efficient, since security prices will reflect all available information (Copeland *et al* 2005 p. 360). It is therefore appropriate to say that rational expectations theory underlies the foundation upon which the efficient market theory of securities prices is built.

One of the earliest applications of the concept of the rational expectations theory is the efficient market theory. The efficient market theory states that the price of a security reflects all relevant information that is available about its fundamental value (Roberts (1967), Fama (1970)). The fundamental value of a security is represented by the discounted future cash-

flow streams which the holder of the security expects to receive. By implication, if a current security price reflects all relevant and available information, as the efficient market theory proposes, the future price cannot therefore be predicted. The implication for price is that current and past information cannot be used by investors to improve their forecasts of future security prices, or indeed be used in valuation models to forecasting security prices. This is more so because efficient market theory assumes that the current security price fully reflects current and past information, thus their implications for future security price distribution. As a consequence, investors, analysts, and fund managers cannot systematically beat the market in their predictions to make superior returns from their investments by using relevant and available price information. The theory also states that new relevant information about companies is instantaneously and fully assimilated into their stock prices. In other words, 'undervaluation' and 'overvaluation' of securities are merely temporary, as the prices of such securities will quickly adjust to their equilibrium values in an efficient market.

Although it may seem that markets can still be efficient, costless, and unbiased, if information is available, the question remains as to whether markets will still be efficient if investors are irrational, for example, if investors are influenced by one or more cognitive biases when making their investment decisions. If investors are overconfident about their valuation models, for instance, how will this influence a future security price? If the impact of overconfidence amongst investors on price is systematic and this causes the price to depart from equilibrium, how long does it take the price to return to rational equilibrium? Furthermore, sufficient conditions for market efficiency such as frictionless markets, no transaction costs and taxes, costless information, and the belief that all market participants have the same distribution for future security price are not characteristics of capital markets in the real world. We know that in practice, transaction costs, exchange fees, taxes, and other forms of charges are incurred by market participants. If this assertion is true, will the market be efficient if in practice it deviates from the conditions listed above? Will the effect of such deviations on price be random in nature and cancel each other out, or will they be systematic such that investors can form profitable trading rules based on them? In addition, the efficient market hypothesis and rational expectations theory do not predict a market where investors hold heterogeneous expectations of future security payoffs. However, we know that in the real world, markets comprise both informed and uninformed investors. What impact would the activities of both informed and uninformed investors in capital markets have on price discovery? Is the number of informed investors large enough to quickly arbitrage away the mispricing caused by uninformed investors, thus returning the price to its rational equilibrium value? Is arbitrage truly a riskless venture? The neoclassical economics theory does not provide plausible answers to the above questions.

1.2 Empirical challenges to the neoclassical model of market efficiency

The publication of Eugene Fama's seminal paper entitled "Efficient Capital Markets: A Review of Theory and Empirical Work" in 1970 was a defining moment in the study of the concept of market efficiency. In this work, Fama brings together existing research in this area and sets the stage for research in the coming years and decades. Throughout the 1970s, the majority of studies using both empirical and theoretical approaches supported the efficient market theory. It was not until the late 1970s that another stream of studies emerged which contradicted and challenged the concept. Jensen (1978) proposes the need for the concept of market efficiency and the methodological procedure used in testing it to be reviewed, due to growing evidence from research showing the inconsistency of the theory. This proposal came as a result of both theoretical and empirical challenges to the efficient market hypothesis which became stronger with the availability of better data and as econometric techniques became more sophisticated.

Some of the early empirical evidence that challenged the efficient market hypothesis preceded its theoretical challenges. The earliest amongst these pieces of evidence is the volatility of stock prices. Shiller (1981) documents that stock prices are far more volatile than can be explained by a model in which these prices are equal to the discounted expected net present value of future dividend streams. In this study, Shiller shows that the high volatility of stock price indices such as the S&P's composite stock price index cannot be justified when those prices are compared to its expected net present value. The calculated expected net present value of prices seems smooth and stable over time, as against the volatility of the actual price series. In addition to this, the author documents that there is no associated new information about future real dividends to justify such large and frequent jumps in stock prices. What this finding tells us is that price movements are not always preceded by the arrival of new information about fundamental value as the efficient market theory states. If they were, there would not be such a large variation between actual prices and their expected values, and the frequency of price jumps would be much more nuanced. The author concludes that the failure of the efficient market model to explain this large price volatility is so dramatic that it cannot possibly be attributed to modelling error, price index problems, or changes in tax laws. Other academics whose works contributed much to this area include LeRoy and Porter (1981).

Long-term stock return reversal is another return anomaly which challenges the propositions of the efficient market hypothesis. De Bondt and Thaler (1985) show that long-term stock returns reversal exists over a time horizon of between three and five years and is predictable. The authors compare the performance of the stocks of two groups of companies

- extreme losers' and extreme winners' stock portfolios. The group of extreme losers comprises those stocks which fall into the lowest return decile, whereas the extreme winners are those stocks that fall into the highest return decile in the past three years. By forming a trading strategy which buys past loser stocks in the prior three years and sells winner stocks over the same period, De Bondt and Thaler show that such a strategy is profitable in succeeding three to five years after portfolio formation. The authors show that the fate of winner and loser stocks is reversed in the three to five years after portfolio formation. In each year of their sample, the authors formed a portfolio of the best and worst performing stocks over the prior three years. Once the portfolios were formed, they computed the return on each of the two portfolios over the next five years. De Bondt and Thaler report that their loser portfolio showed a strong post-formation performance while their winner portfolio showed a relatively poor performance over the same period. Efficient market models such as the capital asset pricing model are not able to explain the difference between the returns of these two portfolios. For example, the improved performance of the loser stocks could not be explained by their risk profile using standard risk adjustment models. However, De Bondt and Thaler explain that the difference noted above is consistent with a behavioural finance interpretation of overreaction of stock prices following initial new information in the market. The authors explain that the market overreacts to both loser and winner stocks, i.e. on average, loser stocks become too cheap before bouncing back after the post-formation year, whereas extreme winner stocks become too expensive, resulting in lower future returns. The evidence from De Bondt and Thaler in this study poses a direct challenge to the weak form of EMH.

Following the findings on long-term reversal in stock returns by De Bondt and Thaler (1985), researchers have documented other forms of stock return anomalies against the propositions of the efficient market hypothesis. Momentum in stock returns is one such anomaly, and can be described as a phenomenon in which stock prices show a continuation in a particular direction for a period of three to twelve months depending on the nature of earnings news or past stock performance. In simple terms, the momentum anomaly means that what goes up (down) in the recent past will continue to go up (down) in the near future. Stocks that have outperformed others in the past three to twelve months continue to do so in the succeeding three to twelve months. If continuation in stock price is a result of its company's recent quarterly earnings outcomes, then the effect is referred to as earnings momentum. Similarly, if continuation in price is a result of the stock's strong performance in the recent past, then the resulting effect is referred to as price momentum. Jegadeesh and Titman (1993) is one of the earliest empirical works to document the existence of momentum in stock returns. The authors examine the returns of individual stocks and report that past

stock returns in the last three to twelve months are able to predict future returns in the same direction. Essentially, this finding says that there is a short-run continuation in stock prices over a period of three and twelve months – stock prices continue to trend upwards for past winner-stocks and downwards for past loser-stocks. If markets are efficient, as held by Eugene Fama and other proponents of the efficient market hypothesis, past security prices and returns will not be able to predict future price, as the information contained in them is already fully reflected in the price. Since the publication of Jegadeesh and Titman (1993), there has been a deluge of publications on this subject which continues to grow. Jegadeesh and Titman (2001) provide evidence on the profitability of price momentum strategies which further supports their 1993 paper on momentum. This work seeks to provide alternative explanations for the profitability of momentum strategies. The authors document that their later evidence supports the idea that momentum profits can be attributed to investors' underreaction to new information in the market. The paper also further posits that the existence of momentum in stock returns could be a result of delayed overreaction to prices which is eventually reversed. In a related paper, Chan, Jegadeesh, and Lakonishok (1999) evaluate the profitability of price momentum strategies based on past returns and find them to be profitable in a short- to medium-term horizon. However, the authors posit that although price momentum strategies are profitable, the extent of their profitability will also depend largely on how well trading costs are managed by investors. If investors must adopt momentum strategies, for such strategies to be attractive, they must be profitable after all the associated costs and fees have been taken into account. Further investigation into momentum profits is provided in another paper by Korajczyk and Sadka (2004). The authors test for the profitability of momentum trading strategies after taking the impact of trading costs on such strategies into consideration. The authors find that the robustness of momentum profits depends on the weighting type adopted during portfolio formation. Their results show that momentum strategies which are based on liquidity-weighted portfolios and a hybrid of liquidity/value-weighted portfolios of highly capitalised companies are profitable even after accounting for transaction costs. But the momentum profits of strategies based on equal-weighted portfolios dissipate when transaction costs are taken into consideration. Chan, Hameed, and Tong (2000) evaluate the profitability of momentum strategies in international equity markets. The authors also find that momentum strategies are profitable even in international stock markets. A more recent paper by Leippold and Lohre (2012) examines specifically the profitability of earnings and price momentum strategies in international stock markets. They find that momentum strategies are profitable in these markets and further state that these profits are improved in high information uncertainty markets. The last statement leads the authors to conclude that momentum profits may be rationalised by a model of investors' underreaction to company fundamental news. This

assertion supports the argument that price momentum will be better explained by behavioural finance models.

Most empirical works in the momentum literature are on the study of momentum profits derived from price momentum strategies, whereas very little has been done on earnings momentum and its strategies. One of the earliest works in literature to study the profitability of earnings momentum in detail is Chan *et al* (1996). By applying a trading strategy based on standardised unexpected earnings (SUE), Chan *et al* (1996) establish the existence of earnings momentum in stocks listed in United States exchanges. Stock prices of companies with positive SUE continue to drift upwards and those of companies with negative SUE continue to drift downwards for between three and nine months after earnings announcement. The standardised unexpected earnings (SUE) metric is a measure of the magnitude of information contained in the most recent quarterly earnings news. It is calculated as the difference between actual quarterly earnings per share and its expected counterpart scaled by its standard deviation in previous quarters. SUE therefore could be thought of as an 'earnings surprise' to market participants on the earnings announcement date. Earnings momentum therefore means that stocks of companies with large and positive SUE continue to outperform stocks of companies with large and negative SUE days, weeks and even months after earnings announcement. Chordia and Shivakumar (2006), in a slight departure from Chan *et al* (1996), examine the relationship between earnings and price momentum, both in time series and cross-section assets tests. The authors document that price momentum is subsumed by the systematic component of earnings momentum in a zero-investment trading strategy that takes a long position in stocks with high SUE and a short position in stocks with low SUE. This finding suggests that although earnings and price momentum are separate phenomena, they are both likely to start as a result of market underreaction to earnings news. Hong, Lee, and Swaminathan (2003) examine the profitability of earnings momentum strategies based on analysts' forecast revisions in eleven international equity markets. They report that although analysts' revisions are persistent in all the countries, the profitability of this strategy varies across them.

The results of the empirical works described above elucidate the flaws inherent in the efficient market hypothesis. They clearly show the persistence of stock return anomalies over the years which therefore cannot be attributed to data snooping bias, improper risk adjustment, sample selection bias, trading costs, or methodology errors. The presence of some anomalies such as momentum has been found to exist across all stock markets around the world and continues to offer a profitable investment strategy to investors and managers. Momentum investment strategies should not be profitable since there is no

evidence that such stocks carry additional risk factors that make them earn extra returns in compensation.

1.3 The advent of behavioural finance: a paradigm shift in financial economics?

The empirical evidence against the efficient market hypothesis described in section 1.2 above and others led researchers to seek alternative interpretations for various anomalies seen in stock returns. Behavioural finance seems to be an alternative paradigm that could offer a plausible explanation as to why these anomalies exist in stock returns. This paradigm shift began when researchers started seeking ways of improving standard finance theory by incorporating more realistic psychological assumptions into empirical finance models. The field of behavioural finance focuses on studies based on the empirical explanations of deviation from two main assumptions of neoclassical economics: investor rationality and homogenous investor assumptions.

In his 2002 paper entitled “A Perspective on Psychology and Economics”; Rabin provides arguments on why greater psychological realism will improve the study and understanding of some phenomena in mainstream economics. He argues that economic models inspired by psychological evidence, which provide the reality of how human beings behave as opposed to theory on how they should behave, will improve the neoclassical economics models. The author shows that behavioural economics is gaining increasing acceptance by economists and the wider academic community. This is not because it is replacing traditional economic theory; rather it has come to improve our understanding of traditional economic assumptions and how economic agents behave. It is in this evolutionary, as opposed to revolutionary, manner that I undertake empirical work to understand the causes of stock market earnings momentum.

Following Rabin (2002a) position above, remarkable progress has been made in providing evidence to support the behavioural finance approach to the study of the behaviour of economic agents. Such evidence comes from the empirical investigation of financial market data and economic-psychology laboratory experiments. Overwhelming results from these investigations show that human cognitive biases and heuristics influence individuals in their decision-making process. Most common amongst these biases and heuristics include the representativeness heuristic, conservatism, overconfidence, self-attribution bias, underconfidence, availability bias, extrapolation bias, the gambler’s fallacy, and the law of small numbers, amongst others. These biases and heuristics have been found to play a crucial role by influencing the way investors form judgement in financial markets (see Asparouhova *et al* (2009), Bloomfield and Hales (2002), Clotfelter and Cook (1993), De Bondt (1993), Kahneman and Tversky (1982)). My thesis employs propositions provided by

two of these works to extend our understanding of what explains earnings momentum in stock returns. The models are the theoretical models of Rabin (2002b) and Barberis, Shleifer, and Vishny (1998).

1.31 Evidence from economics and psychology experiments to support behavioural finance theory

A number of psychological laboratory experiments have helped economics and finance researchers to understand better how investors' behaviour could be influenced by cognitive biases and heuristics. Incorporating assumptions based on these biases and heuristics into their models will no doubt help researchers to explain anomalies found in stock returns. Evidence from these experiments has led academics to believe that although an investor's decision-making process might follow the concept of economic rationality and Bayesian principles, information processing could be influenced by biases and heuristics, thus, error could be introduced into such standard rational decision-making models. Moreover, evidence from these experiments simply shows that individuals do not always make their investment decisions in a manner that suggests that they have Von Neumann-Morgenstern preferences or form judgements in accordance with Bayesian principles. To a certain extent, people behave in a way that shows a systematic departure from both principles when they form judgements.

In their seminal work entitled "Prospect Theory: An Analysis of Decision under Risk", Kahneman and Tversky (1979) further provide insights into the process of decision-making under risk and a specific normative model of rational choice which embeds certain descriptive features regarding how we know these choices are typically made (e.g. loss-aversion, risk-seeking in the loss domain). Their work criticises the expected utility theory and shows several cases of choice problems in which preferences systematically violate the axioms of the expected utility theory. The authors argue that the manner in which the expected utility theory is interpreted shows that it is not a sufficient descriptive model to account for choice under risk. In addition, Kahneman and Tversky (1974) report that when making predictions under uncertainty, individuals are more likely to violate Bayes' rule and the tenets of probability theory. More often than not, people look to draw inferences from non-existent patterns in their decision-making processes. As Kahneman (2011) puts it, we have a profound need for 'coherence' which underlies our philosophical and religious search for a meaning / purpose in life. This leads us to see patterns and destiny, where in fact there is none.

People tend to predict the future outcome of an uncertain situation by examining a small sample of historical data leading to a similar event and drawing a broader conclusion based

on it. In other words, people may see a small sample of historical data as being representative of the entire population from which the sample is drawn. In doing this, they commit the error of representativeness heuristic and do not think that the future outcomes of an event might be a simple random process generated by chance.

Other studies have shown that people update their beliefs according to the 'strength' and 'weight' of new evidence. The 'strength' of a piece of evidence focuses on the signal's salience and extremity, while its 'weight' focuses on the reliability, validity and statistical inference that could be drawn from the evidence. In the face of low 'strength' and high 'weight', individuals tend to react mildly to the evidence, as opposed to someone who is fully Bayesian¹. According to Griffin and Tversky (1992), in revising forecasts, individuals depend much on the strength or the extremity of data and too little on the data's weight, or influence relative to a Bayesian judgement. The authors maintain that, conversely, research shows that individuals are overconfident when there is evidence that shows high 'strength' and 'low' weight, and they react in the same manner in the presence of seemingly representative evidence. Often we see this pattern of behaviour in the popularity of those individuals with outlandish or very intriguing but ultimately baseless opinions. Human beings are rather slow when processing and adapting information which is contrary to the private information they hold about a situation. Therefore, people tend to trust their own individual assessment of a situation better than that suggested by statistical inference. All the behavioural patterns identified above are characteristics of human behaviour which are systematic in nature and not random as efficient market hypothesis suggests.

1.4 Background and motivation for the thesis

The main motivation for this study lies in the continued search for a unified, tractable, and parsimonious theoretical behavioural finance model which is able to explain future stock returns based on an earnings momentum strategy. In the same way that standard finance theory provides models of assets pricing such as the capital asset pricing model (CAPM), behavioural finance theory will have an increasingly relevant impact on the study of finance if it provides models for asset pricing. The contributions of such models in the study of finance should not necessarily be revolutionary in nature, but rather should be complimentary to the standard finance models. It is in this quest for a behavioural finance asset pricing model that I follow the theoretical propositions of Rabin (2002b) and Barberis, Shleifer, and Vishny (1998) to model the behaviour of a representative agent investor in order to explain patterns of future stock returns based on sequences or streaks of quarterly earnings surprise. Both

¹ See Griffin and Tversky (1992) for a full description of the characteristics of the 'weight' and 'strength' of evidence.

models describe the behaviour of an investor whose judgement departs from rational, Bayesian principles when he observes a growing sequence of a binary signal such as quarterly earning outcomes. Both models propose that the departure of this investor from Bayesian principles is a result of the influence of biases and heuristics on the investor. Although the models differ in terms of the biases they believe to be at play in the investor's model, their fundamental assumptions and conclusions are closely related to each other. This thesis therefore investigates the possibility that the predictions of the Rabin (2002b) and BSV (1998) models can be used in the empirical modelling of earnings momentum.

In the behavioural finance literature, the standardised unexpected earning (or quarterly earnings surprise) is the most popular earnings metric used to capture investor behaviour (reaction to price) around earnings announcements. The logic behind this is that the size and sign of the unexpected component of earnings represent the 'true' information contained in the earnings news. The unexpected component of earnings therefore drives future investors' response to earnings news. Following this line of reasoning, early researchers in this area believe that investors consider just the information contained in the most recent unexpected earnings in their earnings forecast models². In contrast, the theoretical models of BSV (1998) and Rabin (2002b) postulate that investors in reality observe sequences or streaks of quarterly unexpected earnings over a period. Both models suggest that investors determine the probability distribution of future earning outcomes based on the distribution of rising or falling earnings in their series. It is at this point that valuation error is introduced into the investor's model. In both the BSV and Rabin models, if an investor observes two consecutive earnings rises or falls, he reduces the probability of observing a similar outcome in the next earnings announcement. The investor does this without considering that the earnings-generating process is a random process and there are equal chances of a rise or fall occurring in future earnings. According to the Rabin (2002b) and BSV (1998) models, the introduction of this error is caused by cognitive biases and / or heuristics³. Thus, in this thesis, I model the impact of rising and falling streaks of quarterly earnings surprises on abnormal returns of S&P500 constituent companies. The thesis focuses more closely on the propositions of Rabin (2002b) than BSV (1998). This is because preliminary tests on my data support Rabin's (2002b) position better than BSV's (1998). Subsequently, I model the role of information uncertainty in the presence of growing streaks of earnings surprises. It is documented in the literature that high information uncertainty firms have lower future returns than low information uncertainty firms. However, if investors are influenced by biases when

² See Chan, Jegadeesh, and Lakonishok (1996), Chordia and Shivakumar (2006), Foster (1977) for full descriptions of the standardised unexpected earnings metric.

³ See chapters 2 and 4 of this thesis for full reviews of the Rabin (2002b) and Barberis, Shleifer, and Vishny (1998) models.

they observe streaks of earnings surprises, it will be interesting to understand the role that information uncertainty plays at that point. Any potential interaction effect between information uncertainty and streaks of earnings surprises could provide a profitable portfolio trading strategy for investors.

In the past, empirical behavioural finance studies have focused on two broad groups of modelling strategies to study the behaviour of investors in stock markets. The first of these groups of models are referred to as noise trader models while the second group are referred to as representative agent models. With the first group of models, behavioural finance researchers believe that there are two categories of investors in capital markets – the informed investor and the uninformed (naïve) investor. In the second group of models, researchers treat all investors as possessing the same information set and behaving in a similar way. Both Rabin (2002b) and BSV (1998) model the representative agent type investor. Again, following in the footsteps of the models, I adopt the representative agent type model to examine the behaviour of investors⁴.

1.5 Research gap

It is established in the literature that standardised unexpected earnings (SUE) explains future stock returns⁵. By applying a trading strategy based on standardised unexpected earnings (SUE) Chan *et al* (1996) establish the existence of earnings momentum in stocks listed in United States exchanges. The authors show that stock prices of companies with positive SUE continue to drift upwards and those of companies with negative SUE continue to drift downwards between three and nine months after earnings announcement. SUE could be regarded as ‘earnings surprises’ to the market participants at the earnings announcement date. However, behavioural finance advocates attribute the ability of SUE in explaining returns to investor underreaction to earnings news. They argue that the sign and size of the unexpected component of earnings news determine the nature and level of investors’ response to the news. Underreaction to earnings news means that investors do not fully incorporate the implications of the information in current news into their forecasting models for future earnings. Behavioural finance tries to offer plausible answers as to why investors underreact to earnings news. Some researchers believe that investors underreact if they are influenced by biases and/or heuristics when they try to understand the information that earnings convey. Understanding the true cause of investor underreaction to earnings news is a challenge for all finance researchers, and of great interest to behavioural finance researchers in particular.

⁴ See chapter 2 of this thesis for the full description and review of the noise trader and representative agent type models.

⁵ See chapter 3 for references for works in the literature that use SUE to explain stock returns drift.

In attempt to further address investor underreaction to earnings news described above, the BSV (1998) and Rabin (2002b) models offer some plausible explanations. The propositions of the BSV (1998) and Rabin (2002b) models suggest that the influence of biases and heuristics on the investor is stronger when the investor observes a sequence or streak of earnings surprises (SUE) than a single earnings surprise at the most recent earnings announcement. But, in a slight departure from BSV (1998), Rabin (2002b) postulates that an investor observing a growing sequence of rising or falling signals at the arrival of each new rate behaves as though he is sampling from an 'urn' of red and blue balls without replacement. This leads the investor to believe that once a ball of a particular colour has been sampled in the current period, the probability of sampling a ball of the same colour in the next time period declines. This is despite the fact that the sampling is entirely a random process. The investor is, however, surprised if in the next time period, a ball of the same colour is sampled. Thus the investor overinfers if he observes three signals (e.g. earnings surprises) of the same sign in a row. Rabin (2002b) therefore argues that when the investor observes a signal of the same sign consecutively, he is likely to be influenced by the gambler's fallacy. The gambler's fallacy causes him to assign a higher probability of sampling that same signal during the third draw in the next time period. This means that the investor will be assigning a higher probability than another investor who is fully rational and Bayesian. The model posits the result of this type of investor behaviour if systematic could cause earnings momentum in stock price.

The two theoretical models described above take our understanding of the investors' response to quarterly earnings news a step further. They do this by proposing that the true driving force behind earnings momentum could be a combined effect of cognitive biases and heuristics on one hand and the distribution of streaks of earnings surprises on the other. The models argue fact that quarterly earnings news in itself (or the individual quarterly earnings surprise) offers little or limited information to investors and other market participants. For both models, the real informativeness of quarterly earnings news lies in its ability to confirm or terminate the continuation of a growing streak of earnings surprises of a particular sign. This confirmation or (termination) of a growing streak of earnings surprises seems to be the true force that drives momentum in stock prices. It is interesting to note that not once in the literature have researchers investigated this route as the possible source of underreaction and overreaction in security prices based on the predictions of these two models (at least as of the time when this research work began). Therefore this gap exists in the extant literature. My thesis seeks to fill this gap through the empirical testing of the impact of sequences or streaks of earnings surprises on the investor. Furthermore, since the existence of earnings-

generated momentum is established in the literature, it is important to establish which of the existing theoretical models explains it best.

Another gap identified in the literature is in the area of the resolution of value uncertainty around the earnings announcement date. Information uncertainty has been identified in the empirical literature to have a positive relation with earnings-generated momentum when it is conditional on the nature of the earnings news⁶. Uncertainty reduces the degree of anticipation of announced earnings and intensifies investors' response to earnings at the announcement date when uncertainty is partially or fully resolved. An initial continuation of positive streaks will be good news to investors, while early termination of such streaks will be bad news. The converse is true for streaks of negative earnings surprises. This is another gap in the existing literature. My thesis seeks to fill this gap by conditioning information uncertainty on the streaks of negative or positive earnings surprises and examine its impact on earnings-generated momentum. In so doing, my thesis contributes to the larger stream of new research in the information uncertainty literature which sheds light on the way financial markets operate.

1.6 Research objectives

In order to fill the research gaps identified in section 1.5, my research objectives are set out below. Firstly, the objective of this study is to validate (or otherwise) the theoretical predictions of the representative agent's investment behaviour using the two models identified in section 1.5. Furthermore, this study will amongst other things compare the BSV (1998) representative agent model with the Rabin (2002b) representative agent model based on how well their predictions fit within my S&P500 constituent sample companies. Additionally, I will employ the propositions of the Rain model to create streaks of earnings surprises (to be used as explanatory variables). Subsequently, these variables will be used to explain medium-term earnings-generated momentum and short-term post-earnings announcement drift in the returns of my sample stocks. Furthermore, I introduce information uncertainty variables conditional upon streaks of earnings surprises into the model to test for any interaction effect they may have on post-earnings announcement drift. Lastly, I investigate whether 'streakiness' in earnings is just a proxy for previously documented variables concerning the resolution of valuation uncertainty surrounding stocks. In order to achieve my objectives I have planned my empirical tests to cover the following:

- i. Modelling the medium-term earnings-generated momentum and reversion cycle from a representative agent's perspective. Comparing the predictions of BSV's model with that of Rabin's model to ascertain which fits best with my data.

⁶ I.e. on either bad or good news - see Zhang (2006a, 2006b), Jang *et al* (2005).

- ii. Examine the influence of the gambler's fallacy on the representative investor. This I do by examining his response to most recent earnings if he observes streaks of positive or negative earnings surprises over twelve quarters.
- iii. Examine the impact of streaks of earnings surprises on a three-day post-earnings announcement drift if the representative investor observes different lengths of streaks of positive and negative earnings surprises over a period of between two and twelve quarters.
- iv. Examine the interaction effect between streaks of earnings surprises and information uncertainty variables in explaining post-earnings announcement drift. I examine whether 'streakiness' in earnings is just one way in which general valuation uncertainty is resolved or whether it constitutes a separate anomaly worthy of study in its own right.

By performing the empirical tests enumerated above (given the hypotheses), I intend to show that streaks of positive (negative) earnings surprises represent that component of the earnings news which presages consistent rises or falls in stock prices. This component is the unexpected part of quarterly changes in earnings which forms the 'true earnings news' by confirming either continuation or termination of streaks of earnings surprises of a particular sign. That component (i.e. the innovation in quarterly earnings) predicts earnings-generated momentum which subsumes the systematic component of price momentum (Chordia and Shivakumar (2006)). If earnings are predictable, it means that the upcoming earnings announcement does not constitute news in its true sense (Bernard and Thomas (1990)). This is because the 'news' has already been anticipated by investors based on an on-going earnings streak.

1.7 Research contributions

My intention for this study is to show how models of representative agents (investors) form their beliefs about firms' earnings. I also intend to show through this study that there is a true underlying component of unexpected earnings (innovation) which drives earnings-generated momentum in stock returns. In this case, I seek to show that the true innovation in quarterly earnings lies in the confirmation or termination of growing positive or negative streaks of quarterly earnings surprises. Furthermore, this study demonstrates that the informativeness of this innovation in quarterly earnings is still valid even in very short holding periods of three days around the quarterly earnings announcement date. The presence of earnings-generated momentum in stocks within this three-day window makes it far less likely that 'streakiness' in quarterly earnings is only found to be value-relevant because of some error in benchmarking returns or in earnings expectations. This is because neither benchmark returns nor earnings expectations typically change much on any given day (Fama (1998)).

This is therefore a confirmation that the earnings-generated momentum in a longer holding period of three months is not a result of external noise in the market.

This thesis makes a number of contributions to the existing literature. Broadly, it contributes to the empirical finance literature by contributing to the development of a richer forecasting model that could be used in practice. More specific contributions from this study to the literature include the following:

- This study highlights potential portfolio strategies which could be exploited within the behavioural finance models by both researchers and practitioners.
- Information uncertainty is known to exacerbate earnings-generated momentum when it is conditioned on the nature of earnings news (Zhang 2006a). With respect to information uncertainty, this study will illustrate the contribution of this characteristic of information uncertainty in improving the potential portfolio strategies when information uncertainty is conditioned on streaks of positive and negative earnings surprises and on their various lengths.
- This study further illustrates that sequences or streaks of earnings changes in the behavioural research literature can be a possible candidate to be used as an explanatory variable for the study of earnings-generated momentum or post-earnings announcement drift. Prior to the time when this study began, there is no known research in the literature that has used this metric. Loh and Warachka's (2012) paper on a cross-section of stock returns and streaks of earnings surprises is a path-breaking endeavour in this area of research. However, my thesis and the study by Loh and Warachka (2012) are fundamentally different, as both follow different approaches.
- One of the major arguments against earnings-generated momentum is that price reactions after earnings announcements and the subsequent momentum effect may not be related to investor underreaction to quarterly earnings news. Some researchers argue that inasmuch as investors may underreact to different news events about firms, it is difficult to single out the exact impact of investors' underreaction to earnings news on stock prices. However, studies involving short window (e.g. daily) events have an obvious advantage in that the daily expected returns are very close to zero, therefore the choice of model for measuring expected returns does not have much impact on the interpretation and inference drawn from

the abnormal returns measured. In light of this argument, I test for the presence of earnings-generated momentum in a very short window of three days beginning a day before the earnings announcement date. The results of this test indicate that earnings-generated momentum is present in the three-day buy-and-hold Fama-French three-factor model adjusted abnormal returns. Thus, the results confirm that earnings-generated momentum exists in both short- and medium-term market price adjustments and might not be attributable to external noise in the market.

- Some researchers argue that because analysts provide forecasts of earnings for a fee, it is unlikely that most investors (especially individual investors) will be buying such information, and as such analysts' forecasts are not representative of investors' expectations of future quarterly earnings. Contrary to this position, my findings show that analysts' forecast of earnings is an appropriate proxy for investors' expectation of future earnings. However, it remains to be confirmed how information contained in an analyst's forecasts disseminates across different investors given that not all investors subscribe to this information source.
- The distribution of earnings surprises in my data sample does not reveal the kind of symmetry predicted in the BSV model. Hence my empirical results support Rabin model over BSV's⁷.

1.8 Outline of thesis

The remaining part of this thesis is organised as follows: chapter 2 presents the literature review on theoretical representative agent earnings momentum models, medium-term earnings-generated momentum and short-term post-earnings announcement drift. The chapter also discusses the two broad classes of behavioural finance models and compares representative agent models with noise trader models. Furthermore, it discusses the various earnings and price momentum strategies and the relation between earnings and price momentum. Chapter 3 describes the data sample and the main methods employed in the empirical analysis. The chapter also discusses the major variables and proxies used in the empirical analyses. Chapter 4 introduces the first empirical analysis and shows the relation between the sequence of annualised quarterly earning changes and three-month buy-and-hold Fama-French three-factor model adjusted returns. The chapter examines various investor responses to prices by regressing different lengths of positive (negative) sequences of earnings changes against the abnormal returns. The tests in this chapter show how the

⁷ See Barberis *et al* (1998) for full details of symmetry between momentum and reversal regimes.

representative investor responds to stock prices when observing positive and negative sequences of quarterly earnings changes under the influence of the gambler's fallacy over a period of twelve quarters. The chapter also compares the BSV (1998) model with the Rabin (2002b) model in terms of their predictions of symmetry in quarterly earnings surprises. I compare the symmetry of the sequences of earnings surprises in my S&P500 sample frame to the predictions of each of the two models. Chapter 5 draws from the conclusions of chapter 4 and tests for the representative investor's response to stock price within three days around the earnings announcement date. This is the period when the influence of the gambler's fallacy on the investor is most intense as he observes the arrival of an earnings surprise confirming or terminating a streak. Additionally, the chapter tests the price impact of positive (negative) streaks of earnings surprises as the streaks lengthen. It also shows the impact of the interaction effect between streaks of earnings surprises and information uncertainty on post-earnings announcement drift. The results of this chapter also show that earnings 'streakiness' is one component in the resolution of valuation uncertainty. Chapter 6 concludes the study, outlines the limitations of this study, and offers recommendations for future research.

Chapter 2

Literature review

2.1 Introduction

This chapter comprises three main parts. The first part reviews the extant literature on momentum anomaly. The momentum anomaly literature covers two main sources of momentum in stock price – earnings momentum and price momentum. Chordia and Shivakumar (2006) define earnings momentum and price momentum thus: “Earnings momentum refers to the fact that firms reporting unexpectedly high earnings subsequently outperform firms reporting unexpectedly low earnings. The superior performance lasts for about nine months after the earnings announcement. Price momentum refers to the strategy that buys past winners and sells past losers, which earns abnormal returns for a period of up to one year after the execution of the strategy”. Earnings and price momentum are two amongst many of such phenomena in which stock prices depart from their fundamental value for weeks, months and even years after relevant information arrives in the market. An earnings momentum trading strategy shows that a portfolio which takes a long position on firms with unexpectedly high earnings (good news stocks) and a short position on firms with unexpectedly low earnings (bad news stocks) earns superior returns. Similarly, a price momentum trading strategy shows that a portfolio which takes a long position on stocks that outperformed in the past (winner stocks) and a short position on stocks that underperformed in the past (loser stocks) earns superior returns (see Chordia and Shivakumar (2006)). Earnings and price momentum remain two of the most pervasive stock returns anomalies in the study of modern finance. There is growing interest in the study of these phenomena: standard finance models have so far been unable to provide plausible explanations for their occurrence in stock returns.

The growing literature on momentum can be classified into earnings and price momentum literature. Although price and earnings momentum are related anomalies, the primary focus of this thesis is on models that can be used to empirically study earnings momentum. I decided to review price momentum literature as it is a very important part of the entire momentum literature. The second part reviews some of the most popular theoretical and empirical behavioural finance models in the literature. The models of interest to this thesis are those we can use to study earnings momentum, hence the choice of the Rabin (2002b) and Barberis, Shleifer, and Vishny (1998) models. The hypotheses tested in this thesis are largely drawn from the propositions of the two models mentioned above. The third part of this chapter reviews the information uncertainty literature.

2.2 Stock returns predictability and return anomalies

Stock returns predictability has received much attention in the literature over the years. This is not just because of its implications for investment practitioners but also because of its important implications for the efficient market models. Known variables with predictive ability in standard finance literature include the financial ratios, such as the earnings-price ratio, dividend-price ratio, and the book-to-market ratio⁸. Furthermore, there is growing evidence in the literature dating back to the early 1980s which shows that past stock returns and earnings surprises (earnings changes) predict stock returns both in time series and cross-sectional data. The past returns and earnings surprises capture large drifts in future returns which other risk factors pertaining to market, size, and book-to-market (common risk factors) are unable to explain.

Researchers have also shown that there is a pattern of return predictability with stock return anomalies such as seasonal anomalies like the January effect, Holiday effect, Halloween effect, day-of-the-week effect, turn-of-the-month, turn-of-the-year effects and others. While there is no consensus amongst researchers on potential explanations for this pattern of predictability, several researchers believe that behavioural finance theories could offer potential explanations for the occurrence of these anomalies. Some of these studies include Harris (1986), Jones, Pearce, and Wilson (1987), Haugen and Lakonishok (1988), Keim and Stambaugh (1984), Ball and Bowers (1986), Ariel (1987), Jaffe and Westerfield (1985), and Gibbons and Hess (1981). The findings of these studies challenge the tenets of market efficiency upon which the standard equilibrium models are formed. In addition, these findings make it important to develop new theories that can account for the anomalies, and this is where the study of behavioural finance becomes appropriate⁹. Some academics argue for the possibility that the presence of these anomalies in stock returns is a mere *ignis fatuus* resulting from incorrect models and data mining (Merton 1985). This makes it even more imperative to test the presence of anomalies in stock returns in out-of-sample data in order to affirm their existence and causes.

Lakonishok and Smidt (1988), using ninety years of daily data from the Dow Jones Industrial Average find a pattern of returns predictability in the stock index. One unique characteristic of this study is the sample period, which is longer than the majority of the previous studies. The authors examine various anomalies including the monthly, semi-monthly, weekend, holiday, end-of-December, and turn-of-the-month anomalies. Their results show the existence of persistent anomalous returns patterns around the turn of the week, the turn of

⁸ See Fama and French (1988), Campbell and Shiller (1988), Goetzmann and Jorion (1993), Hodrick (1992), Lewellen (2004), among others.

⁹ See Foster and Viswanathan (1987), Admati and Pfleiderer (1988a, 1988b).

the month, the turn of the year, and holidays. The results show that average returns are considerably negative on Mondays. There is also a sharp rise in the price of the index around the turn of the month, which is far more than the total monthly price increase. Moreover, there is anomalous price increase from the last trading day before Christmas to the end of the year. Furthermore, the return on the index before holidays is twenty times more than the normal rate of return. It is very unlikely that these anomalous returns behaviours, as documented by Lakonishok and Smidt (1988), are of random occurrence in nature, given the length of sample period. For the same reason, one can also argue that it is unlikely that the existence of these anomalies in returns can be attributed to data snooping, selection bias, or noise. This is more so because recent studies carried out using data samples from other markets show that these anomalies still exist. Such studies include Sharma and Narayan (2014), who find that the turn-of-the-month anomaly affects returns and volatility of returns; Huber and Kirchler (2013) who find positive abnormal returns in post-presidential elections in the United States amongst companies that contribute to the presidential campaign fund of the winner; and Swinkels and van Vliet (2012), who find that amongst portfolio strategies that are based on the five main calendar effects, the turn-of-the-month and Halloween effects are the most profitable. More recently, some studies argue that seasonal anomalies are the result of the impact of investor psychology on stock prices at that time of the year. Bialkowski, Etebari, and Wisniewski (2012) investigate stock returns during Ramadan in fourteen predominantly Muslim countries. The study finds that returns during Ramadan are far higher than at any other time of the year. The authors attribute the superior return to the notion that Ramadan positively affects investor psychology by promoting solidarity and optimism, which extends to investment in these stock markets.

Another set of studies find predictability in stock market returns around major firm events such as the earnings announcement. This is known in the literature as the post-earnings announcement drift (or earnings momentum) in stock returns. Ball and Brown (1968) were one of the first to document the predictability of stock market abnormal returns following earnings announcements. The authors show that after earnings announcements, the cumulative abnormal returns of 'good news' ('bad news') companies continue to drift upwards (downwards) in the days, weeks, and even months following earnings announcement. 'Good news' ('bad news') companies refer to those companies that report actual earning outcomes which are higher (lower) than expected. Reinganum (1981) posits that the predictability of abnormal returns by unexpected earnings is a consequence of poor specification of the benchmark model used in measuring expected returns. Other studies such as Merton (1985) and Ball (1978) take a similar stance to Reinganum. However, in response to Reinganum (1981), Rendleman, Jones, and Latane (1982) provide evidence to

show that abnormal returns following earnings announcements are predictable throughout the 1970s. Rendleman *et al* (1982), using a large data sample, find that the unexpected earnings component of earnings news predicts future abnormal returns. This finding contradicts the findings of Reinganum (1981). In addition to these papers supporting the predictability of returns following earnings announcements, there is a deluge of studies which document the predictability of returns following earnings announcements and proffer reasons for this predictability. They include Bernard and Thomas (1989), who document that their results could not be reconciled with the explanation of incomplete risk adjustment given by some researchers as the reason for the predictability of returns after earnings announcements. The authors rather posit that the delayed price response to new information explanation supports the observed predictability in returns. Furthermore, the authors suggest that the reason for the delayed response to information could be because investors do not fully recognise in their forecast models, the implication of the information in the current earnings news for future earnings. Other authors such as Foster (1977), Forster, Olsen, and Shevlin (1984), Watts (1978), and Jackson and Johnson (2006) amongst others document evidence to show that returns are predictable after earnings announcements. More recent studies using benchmark models such as the Fama-French three-factor models and Carhart (1997) four-factor model also document the presence of return predictability following earnings announcement. This finding is in contrast to the claims that return predictability can be attributed to misspecification in the capital asset pricing model (CAPM).

A number of studies show evidence of predictability in medium- to long-term returns reversal and short-term returns continuation. De Bondt and Thaler (1985, 1987) are amongst the earliest set of studies to show that in long horizons, the reversal of stock returns is predictable. De Bondt and Thaler (1985, 1987) show that in the long term, the returns of extreme prior 'winner' or 'loser' stocks are reversed in the subsequent three to five years. The authors find that extreme prior loser stocks substantially outperform extreme prior winner stocks over a time horizon of about a five-year holding period. Prior 'winner' ('loser') stocks refer to those stocks which consistently posted high (low) excess returns over the past three to five years. The authors attribute the predictability of long-term reversal to the fact that people 'overreact' to series of dramatic and unexpected news events. The 'overreaction' hypothesis maintains that the predictability of long-term returns reversal can be attributed to the belief that investors are swayed by excessive optimism (pessimism) after a series of 'good' ('bad') news about the firm's fundamentals. And, as the saying goes, "whatever goes up must come down and vice versa," hence the long-term reversal. Bremer and Sweeney (1991) also document the predictability of returns reversals in a short horizon of ten days. The authors observe that large extremely large negative ten-day returns are

followed by larger than expected average positive returns in the following days. This price adjustment occurs within a short period of two days and so is devoid of any methodological errors in calculating expected returns. Other authors who document the predictability of return reversal include Chopra, Lakonishok, and Ritter (1992), Brown, Harlow, and Tinic (1988), and Brown and Harlow (1988), amongst many others. Short-term return continuation, otherwise known as momentum in stock price, is another predictable return anomaly widely studied in literature. Stocks that performed well (winners) in the past three to twelve months tend to perform well in the subsequent three to twelve months and vice versa¹⁰.

If the assumptions of the efficient market hypothesis hold true, these anomalies should not be predictive for a number of reasons. First, since the efficient market hypothesis assumes *new* information is instantaneously incorporated into price, historical information should not be able to predict future prices. Second, if the anomalies in returns are random events, then they will cancel each other out and should not show systematic pattern in their occurrence. So far, there is no plausible explanation by the proponents of the efficient market theory to account for the predictability of returns around seasons and company events. Researchers find that empirical evidence does not support other arguments for the predictability of returns around these periods such as methodological flaws and the misspecification of benchmark models. The predictability of returns using past price and earnings information is particularly a direct challenge to the weak and semi-strong forms of efficient market hypothesis respectively. Additionally, the predictability of returns has been tested out-of-sample and found to be persistent over the years and across different markets, which rules out the possibility of data snooping being responsible for the predictability.

2.3 Momentum anomaly and its trading strategies

Although the primary focus of this thesis is earnings momentum models, it is however pertinent for me to review earnings momentum as well as price momentum literature, because, until recently, the price momentum phenomenon remained the most widely studied and applied of the two momentum anomalies. However, this trend is changing as more research on earnings momentum emerges which shows new evidence both on its existence and how it can be exploited by investors and investment practitioners.

Given the nature of the predictability of stock returns following earnings announcements and in periods of bad and good market performances, research shows that investors and investment practitioners seek to exploit any abnormal profit opportunities that may exist in these anomalies. They do this by creating stock trading strategies that are based on

¹⁰ See Jegadeesh and Titman (1993, 2001).

predictable phenomena such as earnings momentum and price momentum. In this regard, momentum anomalies provide some of the most popular trading strategies. There are two fundamental momentum trading strategies – the price momentum and earnings momentum strategies. Between these two strategies, price momentum has received far more attention than earnings momentum both in research and as an investment strategy. The profitability of momentum strategies has also been the focus of various researchers across different markets. The evidence from these researchers shows that momentum strategies are profitable in the majority of stock markets in the world.

2.3.1 Price momentum strategies

Jegadeesh and Titman (1993) is one of the earliest empirical studies to document the existence of momentum in stock returns. The authors examine the returns of individual stocks, and report that past stock returns in the prior three to twelve months are able to predict future returns in the same direction. Put another way, this finding says that there is a short-run continuation in stock prices over a period of three to twelve months; stock prices continue to trend upwards for past winner-stocks and downwards for past loser-stocks within this time horizon. The authors find that the price momentum strategy, which is a strategy that buys (sells) prior winner (loser) stock, has positive returns over a period of between a three- and twelve-month holding-period. By employing various mixes of formation and holding period strategies (producing a total of thirty-two different portfolios), the authors show that the strategy produces positive returns throughout their sample period. Jegadeesh and Titman (1993) posit that price momentum is not related to delayed price reactions to common factors rather their finding suggests that price momentum relates to delayed price reactions to some particular firm-specific information. Given that the price momentum strategy is only positive within the first twelve months after portfolio formation and negative afterwards, Jegadeesh and Titman argue that the most likely explanation for this is that transactions by investors who buy past winners and sell past losers cause the price to move away from its fundamental value temporarily which then causes a subsequent price overreaction. An alternative explanation is that price momentum is a consequence of investors underreacting to information regarding the short-term prospects of firms and overreacting to information about their long-term prospects. This is more so because the nature of the information (such as earnings forecasts) which investors use to assess firms' short-term prospects is different from the nature of the more complex information set which investors use to assess firms' long-term prospects. Advancing their earlier study on price momentum, Jegadeesh and Titman (2001) further examine the findings in their 1993 paper to ascertain whether the strategy remains profitable. In this latter study, the authors seek to provide alternative explanations for price momentum profits using out-of-sample data. They

document that evidence from current findings supports the idea that momentum profits can be attributed to investors' underreaction to new information about firms' prospects. Again, patterns of returns similar to those in Jegadeesh and Titman (1993) are seen in their 2001 study.

In a study similar to Jegadeesh and Titman (1993, 2001), Chan, Jegadeesh, and Lakonishok (1999) evaluate the profitability of price momentum strategies and find them to be profitable in the short- to medium-term horizons. However, the authors posit that although price momentum strategies are profitable, the extent of their profitability depends largely on how well investors manage their trading costs. In contrast to Chan, Jegadeesh, and Lakonishok (1999), Korajczyk and Sadka (2004) test the profitability of price momentum trading strategies after taking into account the impact of trading costs on such strategies. The authors find that the robustness of momentum profits depends on the weighting type adopted during portfolio formation. Their results show that momentum strategies which are based on liquidity-weighted portfolios and a hybrid of liquidity/value-weighted portfolios of highly capitalised companies are profitable even after accounting for transaction costs. However, the momentum profits of strategies based on equal-weighted portfolios dissipate when transaction costs are considered.

Chan, Hameed, and Tong (2000) evaluate the profitability of price momentum strategies in international equity markets. The authors also find that price momentum strategies are profitable even in international stock markets. The finding therefore supports the argument that price momentum anomaly cannot be thought of as a localised market effect. A more recent paper by Leippold and Lohre (2012) examines specifically the profitability of price momentum strategies in international stock markets. They find that price momentum strategies are profitable in these markets and further state that the profits improve in high information uncertainty markets. The last statement leads the authors to conclude that momentum profits may be rationalised with a model of investors' underreaction to firms' fundamental news. This assertion supports the argument that price momentum will be better explained by behavioural finance models. The findings on price momentum are in direct violation of the tenets of the efficient market hypothesis – the weak form of market efficiency in particular. If the markets are efficient, as described by Eugene Fama and other proponents of market efficiency in the 1970s, past security prices and returns will not be able to predict future prices, as the information contained in them is already fully incorporated into the price.

2.3.2 Earnings momentum strategies

Early work on earnings momentum was first documented by Ball and Brown (1968). Ball and Brown indicate the existence of a possible relation between the sign and magnitude of the unexpected earnings and subsequent stock price adjustment. The authors document that following an earnings announcement, cumulative abnormal returns tend to drift upwards (downwards) for stocks that have good (bad) earnings news. Good earnings news is reflected in unanticipated earnings increases and bad earnings news is reflected in unexpected earnings decreases. If there is a possible relation between the sign and magnitude of unexpected earnings and a stock's returns after earnings announcement, then a trading strategy may exist which will exploit this relation. Other studies such as Foster (1977), and Foster, Olsen, and Shevlin (1984) show that this relation exists in a time series, while Latane and Jones (1979), Bernard and Thomas (1989), Bernard, Thomas, and Wahlen (1997), Chan, Jegadeesh, and Lakonishok (1996), Chordia and Shivakumar (2006), and Liu, Strong, and Xu (2003) show that the relation also exists in a cross-section of stock returns.

Chan, Jegadeesh, and Lakonishok's (1996) paper is one of the earliest studies to provide in detail the effectiveness of an earnings momentum-based trading strategy. By implementing an earnings momentum-based strategy using standardised unexpected earnings (SUE), Chan *et al* establish the existence of earnings momentum anomaly in stocks listed in United States exchanges. Stock prices of companies with positive SUE continue to drift upwards and those of companies with negative SUE continue to drift downwards for between three and nine months following the earnings announcement. Therefore, the earnings momentum anomaly implies that stocks of companies with large and positive SUE continue to outperform stocks of companies with large and negative SUE in the days, weeks and even months after earnings announcement. The relation between the size and sign of SUE and the magnitude of drift in returns following earnings announcement is found to be a positive correlation.

Chordia and Shivakumar (2006), in a slight departure from Chan *et al* (1996), examine the relation between earnings momentum and price momentum in both time series and cross-sectional tests. The authors document that the explanatory power of the price momentum proxy is subsumed by the systematic component of the earnings momentum proxy in a zero-investment trading strategy that takes a long position in stocks with high SUE and a short position in stocks with low SUE. According to the authors, both proxies individually explain abnormal stock returns, but the earnings momentum effect is more intense and dies out more quickly than the price momentum effect. This finding suggests that although earnings and price momentum anomalies are separate phenomena, they are most likely to start as a

result of market underreaction to earnings news. Furthermore, an alternative explanation for the above is that since momentum in the stock price is strongest around the earnings announcement, it is therefore not surprising that the earnings momentum strategy subsumes the price momentum strategy close to earnings announcement dates. This may be because the earnings momentum strategy is strengthened by an incomplete response to information in the short-term earnings announcement. Also, as Chan *et al* observe, the reason why the price momentum strategy may last longer than the earnings momentum strategy may simply be because it exploits the slow response to the market's wider information set and even the firm's longer-term profitability prospects. Hong, Lee, and Swaminathan (2003) examine the profitability of earnings momentum strategies based on analysts' forecast revisions in eleven international equity markets. The authors report that although analysts' revision is persistent in all the countries, the profitability of this strategy varies across them. Liu, Strong, and Xu (2003) test drift in returns using all earnings momentum metrics such as those based on time series of earnings (historical earning outcomes), market prices, and analysts' forecasts. They find that each of these three measures individually explains the earnings momentum anomaly.

2.3.2.1 Evidence of post-earnings announcement drift in the literature

Post-earnings announcement drift means that stock returns drift in the same direction as the earnings surprise for some time after earnings announcement (Loh and Warachka (2012), Hew *et al* (1996)). Stock returns drift upwards for firms with positive earnings surprises while the opposite happens to firms with negative earnings surprises. This phenomenon has proved to be a challenge to the efficient market hypothesis. The existence of post-earnings announcement drift was documented in the literature even before the 1970s. Jones and Litzenberger (1970) in their study of two groups of firms find that there is significant post-earnings announcement drift for firms with positive quarterly earnings and these firms outperform the market in ten different instances. They argue that if at quarterly earnings announcement dates, investors face earnings that are significantly higher than anticipated; this will lead the investors to make an upward revision of the fundamental value of the firms' common stocks.

Foster (1977), in his study of the times series behaviour of quarterly earnings, observes that there is a significant relation between the sign and size of the unexpected earnings and the cumulative residual (abnormal) returns in a -20 day to +20 day trading window around the earnings announcement. He finds that the time-series models that incorporate seasonality in quarterly earnings show more significant association with the cumulative residual returns than the non-seasonality forecasting models. Foster, Olsen, and Shevlin (1984) report that

the systematic post-earnings announcement drifts in returns are only found in a sub-set of earnings expectations models. They document that price-based earnings expectations models show no systematic post-announcement drifts within a [+1 to +60] trading day period. However, they also find that for the class of earnings expectations models that capture systematic drifts in returns in a [+1 to +60] trading day period, the drift is present in each year of the sample period (1974 – 1981). They report that the sign and magnitude of the unexpected earnings surprise explain the cumulative abnormal returns; the more positive (negative) the unexpected earnings change, the more positive (negative) the post-earnings announcement drift. In older literature, many arguments on why post-earnings announcement drift persists dwell mainly on whether the model used to capture the market's expectations of earnings is appropriate or whether there is a misspecification of the regression model or the proxies for earnings surprises or the subsequent price movements are incorrect. Foster *et al* (1984) explore this line of argument fairly exhaustively and confirm the presence of post-earnings announcement drift in all, regardless of which expectation and benchmark models are used. So the question is more about why post-earnings announcement drift occurs rather than if it does. Another important piece of research by Hew *et al* (1996) finds evidence that post-earnings announcement drift is present amongst small firms but not large firms in 206 firms listed on the London Stock Exchange between 1988 and 1993. The authors offer no explanation for the disparity between the small and large firms' results. However, in contrast to the finding of Hew *et al*, Liu, Strong, and Xu (2003) report the presence of post-earnings announcement drift in the UK markets. They use various measures of earnings surprise based on time series, market prices, and analysts' forecasts of earnings to confirm that stock returns drift in the direction of the earnings surprise after earnings announcement. They also document that each of the earnings surprise measures significantly explains post-earnings announcement drift in these stocks. Liu *et al*'s (2003) study is essentially an extension of Hew *et al*'s (1996) work, albeit their work covers a larger number of firms (835 firms) and over a longer period of time (1988 – 1998). Unlike the Hew *et al* (1996) results, Liu *et al* (2003) find post-earnings announcement drift to be present in both small and large firms' stocks. Truong (2011) shows evidence of post-earnings announcement drift in the Chinese stock market between 1994 and 2009.

2.3.2.2 Post-earnings announcement drift and earnings surprise measures

There are many papers in the finance literature which show evidence that earnings surprises are able to explain the post-earnings announcement drift seen in stocks returns after the earnings announcement¹¹. There are also divergent opinions amongst academics and practitioners as to what is the most appropriate measure of earnings surprise which will effectively capture investors' expectations of future earning outcomes. It is absolutely crucial to find a metric which captures the full change in the market's expectations of earnings when earnings numbers are revealed on announcement dates. Only such a measure can give an accurate explanation of stock price behaviour following earnings announcement.

Livnat and Mendenhall (2006) show that post-earnings announcement drift is significantly larger when earnings surprise is calculated using analysts' forecasts and realised earnings from the I/B/E/S database than when using models that are constructed based on times series of historical actual earnings. They report that the disparity between the two measures lies in the differences between analysts' forecasts and the times series model as measures of investor expectations of future earnings. Furthermore, the authors document that since the two measures of earnings surprise lead to different return patterns around future earnings announcements, it is likely that they capture different types of mispricing in stock prices. Rather than following Livnat and Mendenhall's (2006) mispricing line of argument, one may wish to consider the weight and strength of the information content of analysts' forecasts in contrast to that of the time series of historical actual earnings. It is well known that investors regard forecasts by analysts and other investment professionals very highly (Gleason and Lee 2003). This is more likely because the large information set which is available to analysts to incorporate into their forecasts will be judged to be more informative than the stale historical earnings. Again, analysts revise their forecasts on a monthly basis to incorporate any new information that may change firms' future prospects. By intuition, it is not surprising that analysts' forecasts display a larger change in investors' expectations of earnings outcomes than do the historical actual earnings. In a study closely related to Livnat and Mendenhall (2006), Lerman, Livnat, and Mendenhall (2007) compare the predictive ability of various earnings surprise proxies measured using historical time series of the earnings model and analysts' forecast-based model. The authors show that the post-earnings announcement drift is significantly larger when earnings surprise is measured using the analysts' forecast model than when the historical time series model is used. They also report that combining both models improves the predictive power for post-earnings announcement drift over and above the individual models. Liu, Strong, and Xu (2003)

¹¹ See Liu *et al* (2003), Loh and Warachka (2012).

document that of the three measures of earnings surprise they used; the price-based earnings surprise measure captures the strongest drift in returns around earnings announcement. They also report that in a two-dimensional analysis, the drift associated with the price-based earnings surprise measure subsumes the drift associated with the other two earnings surprise measures. This may suggest that the price-based measure of earnings surprise contains a broader information set encompassing the information sets of both the times series and analysts' forecasts-based measures of earnings surprise.

Loh and Warachka (2012) take the study of post-earnings announcement drift to a new level with their introduction of a new metric which has not been previously used in post-earnings announcement drift research. The new metric is the streaks of earnings surprises, put into different categories according to their length and sign. The authors find that investors underreact to streaks of earnings surprises of the same sign in similar manner to how they underreact to individual quarterly earnings surprises, but with higher intensity. The authors argue that if the most recent earnings surprise confirms an existing streak, the post-earnings announcement drift is significant and strong, whereas the post-earnings announcement drift is weak if a streak is terminated at the arrival of the most recent earnings surprise. They conclude that post-earnings announcement drift has a time series component that is consistent with the gambler's fallacy, as Rabin (2002b) predicts¹².

Zolotoy (2012) models the relation between stock prices and accounting earnings by allowing for divergent opinions amongst investors and other market participants in measuring the expected company earnings. In a number of ways this work is similar to the work of Lerman *et al* (2007) reviewed earlier. Zolotoy introduces a new measure of earnings surprise which he terms 'implied earnings surprise'. This measure is a weighted average of the random walk, time series, and the analysts' measures of earnings surprise. The weights of the individual earnings surprise measures are directly taken from the stock price. The author finds that measures from the random walk and the analyst forecast models have different forecast accuracy. The implied measure of earnings surprises is associated with the highest post-earnings announcement drift, over and above that associated with the measures of both the time series and analysts' forecast models. He argues that using the implied earnings surprise model encompasses the beliefs of different types of investors in the market. For example, the implied earnings surprise measure incorporates the level of investor sophistication as well as the type of model that the investor uses in forecasting earnings. He goes further to note that the announcement day stock returns will reflect a

¹² See detailed review of Rabin (2002b) in chapter 4.

mixture of earnings news, as measured by the plethora of earnings forecast models used by market participants.

The debate amongst academics and researchers on the best measure of earnings surprise that fully captures investors' expectations about company earnings is as old as the post-earnings announcement anomaly itself. There is no consensus as to which of the models best captures investors' change in expectations when the earnings outcomes are announced.

2.3.2.3 Is post-earnings announcement drift an underreaction to changes in analysts' and investors' expectations?

Although there are many studies on post-earnings announcement drift, the question still remains as to what causes the phenomenon. There are divergent opinions as to what causes stock prices to drift for days or even months after earnings announcement in the same direction as the earnings surprise. Many academics argue that post-earnings announcement drift occurs as a result of the analysts' and investors' underreaction to stock prices as a result of the change in their expectations of earnings at the earnings announcement date. Others argue that post-earnings announcement drift occurs as a result of misspecification in models that academics and researchers use to calculate the investors' *ex ante* earnings expectations (Bernard and Thomas (1989), Jacob *et al* (2000)). Still others argue that post-earnings announcement drift is explained by risk factors, such as liquidity, which the expectation models do not capture (Sadka 2006). Sadka explains that the unexpected systematic component of firm-level liquidity risk is priced within the context of post-earnings announcement drift portfolio returns.

The most common explanation for the cause of post-earnings announcement drift in the research literature is analyst and investor underreaction to earnings news. Underreaction to earnings announcements means that the average stock return in the period following good news (higher than expected earnings realisation) is larger than the average stock return in the period following bad news (lower than expected earnings realisation). The difference in average returns between the two groups of stocks shows that the market does not fully incorporate the information contained in current earnings news for future earnings forecasts. Evidence in the literature shows that both analysts and investors underreact to earnings news, and this underreaction leads to post-earnings announcement drift in the short term¹³. Bernard and Thomas (1989, 1990), Freeman and Tse (1989), Mendenhall (1991), and Wiggins (1991) are among some of the early papers to show that post-earnings

¹³ See Abarbanell and Bernard (1992), Constantinou, Forbes, and Skerratt (2003), Mikhail, Walther, and Willis (2003).

announcement drift could be a result of an incomplete initial response of market participants to the earnings announcement. Mande and Kwak (1996) find strong evidence suggesting that Japanese analysts underreact to information in earnings announcements and this underreaction leads to post-earnings announcement drift in the Japanese market. The authors argue that the underreaction is strongest amongst firms with predominantly permanent components in their earnings. Comparing the level of underreaction amongst earnings prepared under Japanese GAAP and US GAAP, the authors show that analysts' underreaction (and consequently post-earnings announcement drift) is stronger when US GAAP is used. They also find that US analysts discount information contained in earnings to a larger degree than their Japanese counterparts do. Bernard (1992) reviews a variety of evidence present in the prior literature on market efficiency and company earnings. The survey concludes that on average the initial response to earnings announcements is an underreaction. This underreaction to earnings announcements by investors is the cause of the subsequent drift in stock prices.

Abarbanell and Bernard (1992) argue that analysts' underreaction to earnings announcements can explain about half of the magnitude of drift in stock prices following earnings announcements. The authors believe that security analysts' behaviour partially explains stock price underreaction to earnings news. In a review paper, Kothari (2001) shows that post-earnings announcement drift (which has been persistent in tests carried out over the prior thirty years) appears to be consistent with the investor underreaction argument. The author suggests that post-earnings announcement drift is a result of investors' underreaction to value-relevant information in earnings announcements. He suggests that alternatively post-earnings announcement drift may be a result of investors' sluggishness in the processing of earnings information. Chordia and Shivakumar (2005) argue that part of the underreaction to earnings surprises can be attributed to the 'inflation illusion' hypothesis proposed by Modigliani and Cohn (1979), which posits that stock market investors fail to take into consideration the effects of inflation on nominal earnings growth when valuing stocks. Modigliani and Cohn (1979) maintain that investors do not adjust their forecasts for earnings growth when inflation rises, even though they adjust their discount rates. Chordia and Shivakumar (2005) claim that there is a possibility that earnings growth measured by SUE in response to inflation will vary across stocks and this may in part be the cause of post-earnings announcement drift.

So far there is no consensus among academics and practitioners as to the exact cause of post-earnings announcement drift. A majority of the studies carried out in this area over the years suggest strongly that the post-earnings announcement drift anomaly is at least in part caused by analysts' and investors' underreaction to value-related information in earnings

news. However, the objective of this study is not to find what causes post-earnings announcement drift. It is rather about demonstrating whether this pervasive anomaly is present in large stocks as represented by my S&P500 constituent companies by employing the Rabin (2002b) propositions.

2.3.3 Momentum strategies: payoffs and profits

The interest in the study of earnings and price momentum anomalies does not just arise because their existence in security returns remains a puzzle for the efficient market theory but also because they can be exploited to form profitable portfolio trading strategies. Both earnings and price momentum strategies have shown to be profitable in most developed markets, especially in the United States, United Kingdom, Australia, etc. There are also reported cases of earnings and price momentum anomalies in international, emerging, and frontier markets such as China and South Africa, although both strategies are profitable in only a handful of these markets. Moreover, the quest to explain momentum profits continues to attract differing opinions from behavioural finance theorists and efficient market supporters. Therefore, the task of finding models that can better explain momentum profits lies at the centre of this interest in the study of momentum anomalies. Providing plausible behavioural answers that fully explain momentum profits will be a major contribution to the finance literature.

Behavioural finance theorists argue that profits from momentum strategies could be attributed to systematic mispricing of securities by investors due to psychological bias¹⁴. In contrast, efficient market researchers such as Conrad and Kaul (1998) argue that the profitability of momentum strategies could be entirely due to cross-sectional variations in expected returns rather than any predictable time series dependence in stock returns as Jegadeesh and Titman (1993) indicate. Furthermore, Fuertes *et al* (2009) argue that since momentum profits are not normally distributed, they could be partial compensation for systematic negative skewness risks. This line of argument is in accord with the efficient market theory. The authors further argue that although non-normality risks are matter for consideration in their analysis, a large proportion of the momentum profit still remains unexplained. And, as they indicate, the unexplained part of momentum profits may find explanation in the behavioural finance models.

Some proponents of the efficient market hypothesis argue that the profitability of Jegadeesh and Titman's (1993) price momentum strategies could be attributed to data snooping or some other unexplainable market microstructure effects. They argue that techniques such as

¹⁴ See Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), Hong and Stein (1999).

'skipping' weeks between formation and the test portfolios adopted by Jegadeesh and Titman could be viewed as an attempt at data snooping¹⁵. However, to establish that the original results in Jegadeesh and Titman (1993) are not a product of data snooping, Jegadeesh and Titman (2001) evaluate different explanations for the profitability of their 1993 study using an extended data sample. Their results are consistent with that of their earlier work, and show that price momentum strategies are still profitable even in the late 1990s. In this later study, Jegadeesh and Titman show that past winner stocks continue to outperform past loser stocks by about the same margin documented in Jegadeesh and Titman (1993). The six-month price momentum strategy of Jegadeesh and Titman (1993) earns abnormal returns of about 1% per month over the 1965 to 1989 sample period. Additionally, Jegadeesh and Titman (2001) find that the price momentum strategy is significantly profitable in the first twelve months following the portfolio formation date, and the cumulative returns declines thereafter.

Chan, Jegadeesh, and Lakonishok (1996) present evidence which shows that both earnings and price momentum strategies are profitable. By creating a price momentum strategy which sorts stocks using prior six-month returns, the authors show that this strategy yields spreads in returns of 8.8% over the subsequent six months. Again, an earnings momentum strategy which ranks stocks using a moving average of past revisions in analyst consensus estimates of earnings produces a spread of 7.7% cumulatively over the next six months. The authors find that in general, the price momentum strategies tend to be stronger and more long-lived than the earnings momentum strategies. In a related study, Chordia and Shivakumar (2006) find that the SUE portfolio (earnings momentum strategy) over a sample period from January 1972 to December 1999 yields a monthly average abnormal returns of 0.9% while a past return portfolio (price momentum strategy) yields an average of 0.76% per month. The above result (price momentum strategy) is consistent with Grundy and Martin (2001), who document a return of 0.86% per month over the sample period 1962 to 1995 and Chordia and Shivakumar (2002) who report a return of 0.73% per month over the sample period 1963 to 1994 for price momentum strategies. Foster *et al* (1984) document that an annualised payoff of 25% is realised from earnings momentum strategies.

In contrast to other studies, Chordia and Shivakumar (2002) show that profits from momentum strategies are explained by common macroeconomic variables that are related to the business cycle. They report that their analysis uncovers the time variation exhibited by momentum strategy payoffs and claim that returns to momentum strategies are positive during expansionary periods and negative during recessions. More recent literature

¹⁵ See Black (1993), MacKinlay (1995), and Lo and MacKinlay (1988).

continues to show that both earnings and price momentum strategies are profitable across different markets, including international equity markets¹⁶. This is despite the fact that different methodologies have been used both to construct the earnings momentum proxy in particular, and benchmark models for *ex ante* returns. Therefore one cannot argue that momentum profits are a consequence of data snooping or methodological error. What is certain from the literature is that there is no consensus amongst academics as to the sources of momentum profits. Behavioural finance advocates the belief that momentum profits are down to investor sentiments and the argument for the influence of heuristics and cognitive biases seems very plausible.

2.3.4 Relation between earnings and price momentum anomalies

There are not many studies in the literature that have examined the relation between earnings and price momentum anomalies. However, it is vital to examine the relation between the two anomalies, since the interest in both as trading strategies lies in the fact that there is a continuation in the price of the stock, and the trader may want to take advantage of such continuations. Evidence shows that there is some relation between earnings and price momentum. Chordia and Shivakumar (2006), studying the relation between earnings and price momentum, create an earnings momentum portfolio that capture price momentum using a cross-section of stocks on the NYSE-AMEX markets. The authors document that price momentum is subsumed by the systematic component of earnings momentum, whereas price momentum does not subsume the earnings momentum component. They argue that this finding may suggest that 'earnings surprise' (the earnings momentum proxy) is really a part of the overall non-diversifiable (systematic) risk. They find that the predictability of future returns based on past returns is subsumed by the systematic component of the earnings surprise proxy (in a well-diversified portfolio) in cross-sectional tests. The firm-specific part of the earnings surprise cannot subsume the price momentum, which itself is likely caused by a collection of non-firm-specific factors.

In addition to the findings of Chordia and Shivakumar (2006), more studies document that different proxies of earnings momentum show different levels of predictability on a cross-section of stock returns. Again all the different proxies show that price momentum is subsumed by the systematic component of earnings momentum anomaly¹⁷. This finding is consistent with that of Chan *et al* (1996) which documents that since earnings provide on-going information about the performance of a firm and its prospects, market reactions are highest around earnings release. Therefore it not surprising that the momentum effect is

¹⁶ See Hou, Peng, and Xiong (2009), Leippold and Lohre (2012).

¹⁷ See for example Liu *et al* (2003).

usually strongest around subsequent earnings announcements when investors are reconciling their forecasts with the earnings figures. Chan *et al* further show that in a univariate analysis, the prior return (price momentum proxy) and earnings surprise (earnings momentum proxy) variables both have marginal predictive powers for future returns. However, in a cross-sectional regression, they find the explanatory power of prior returns to be 5.7%, but on introducing past earnings surprises into the regression model, the predictive power of prior returns drops to 2.9%. This confirms evidence reported in Chordia and Shivakumar (2006) that price momentum is subsumed by the systematic component of earnings momentum. Therefore, one can say that price and earnings momentum are two separate phenomena. Both are, however, additive security returns anomalies and not different faces of one anomaly. They are not one phenomenon viewed from alternate perspectives or able to be subjected to a common explanation. Furthermore, if the price momentum anomaly can be subsumed by the earnings momentum anomaly that suggests that both anomalies draw upon the market's underreaction to information about firms' future earnings and prospects.

Hong, Lee, and Swaminathan (2003) find that an interesting relation exists between price and earnings momentum in eleven international equity markets. The authors show that price and earnings momentum are present in six of the eleven countries studied (momentum is present in Australia, Canada, France, Germany, Hong Kong and the United Kingdom but not in Malaysia, South Korea, Japan, Singapore or Taiwan). One remarkable finding of this paper is that price momentum exists only in those markets where earnings momentum is profitable. This is a clear indication that there is a strong link between the two momentum anomalies. In a more recent paper, Schneider and Gaunt (2012) examine the relation between price and earnings momentum in the Australian stock market. They provide a comprehensive examination of earnings momentum in the Australian market and also analyse its interaction with price momentum. However, unlike the findings of Chordia and Shivakumar (2006), the authors document that neither earnings momentum nor price momentum subsume each other. They find the relation between the two momentum anomalies is such that each of them has independent explanatory power for future stock returns.

2.3.5 Observed differences in the persistence of the two momentum strategies

Chan *et al* (2006) observe that there is a difference in persistence between the two broad momentum strategies – price and earnings momentum. They argue that the uncertainty underlying the short-horizon measures of profitability used in earnings momentum strategies is resolved relatively quickly. This is because the frequency with which quarterly earnings

announcements are made means that uncertainty about a firm's future prospects is either partially or fully resolved with every future announcement. On the other hand, prior returns (price momentum strategy) reflect a more broad set of market expectations that are not related to near-term profitability alone. However, the price momentum strategy incorporates a far larger information set (including earnings news) than the earnings momentum strategy. This information set includes all other news about a firm's events that reflect the totality of its long-term profitability expectations. Thus, with the price momentum strategy, one can see why it takes longer for the new information 'package' to play out fully in stock prices.

Jackson and Johnson (2006) report that although the behaviour of the two momentum strategies differs; they share a common intuitive interpretation that the market underreacts to information. They document that the different underreaction anomalies appear to have different characteristic time scales in terms of how long the drift persists. Jackson and Johnson argue that price momentum strategy persists in a twelve-month returns but declines rapidly afterwards. However, an earnings momentum strategy using analysts' forecast revisions as a proxy shows that earnings momentum effects persist for at most six months. Jegadeesh and Titman (1993) report that price momentum payoffs persist significantly for as much as twelve months after portfolio formation. This result is consistent with the finding of Chordia and Shivakumar (2006), who test the robustness of Jegadeesh and Titman's result by varying the holding period between three, six, and twelve months. Hong *et al* (2003) document that the results of their analysis of eleven international equity markets are consistent with the predictions of Barberis, Shleifer, and Vishny (1998) that price momentum exists only in those countries where earnings momentum is profitable. In countries where momentum strategies are profitable, they report that the magnitude of price momentum profits is stronger than that of earnings momentum profits.

With respect to the persistency of price and earnings momentum strategies, a number of inferences can be made. First, the earnings momentum strategy generates more abnormal returns than the price momentum strategy very early after formation date. The reason is not clear although, as mentioned earlier, the earnings momentum strategy is formed based on a single piece of firm information which arrives more frequently. Second, although the earnings momentum strategy brings more intensity than the price momentum strategy, its profitability declines more rapidly. From the literature, evidence shows that the earnings momentum strategy is not profitable beyond a six-month holding period, whereas the price momentum strategy is profitable for up to twelve months.

2.4 Behavioural finance models of investor overreaction and underreaction to new information

Building on psychological and empirical evidence, behavioural finance scholars have come up with theories which seek to explain the anomalies of both continuation in short- to medium-term returns and long-term reversals in a cross-section of stock returns. Evidence shows that there is a positive autocorrelation of stock returns for a period of between three and twelve months after a positive 'earnings surprise; (Bernard and Thomas (1990)). This phenomenon, otherwise known as earnings momentum (post-earnings announcement drift), is thought to be the result of investors' underreaction in processing the information contained in earnings news. On the other hand, overreaction to a string of good or bad news events leads to a long-term reversal in stock returns over a horizon of between three and five years (De Bondt and Thaler (1985)).

In behavioural finance, we can identify two broad contrasting types of modelling strategies that researchers employ in studying investors' behaviour in reaction to information about firms and their stocks. These modelling strategies are the representative agent models and the noise trader models. These two types of model each have their own strengths and weaknesses. A selected list of theoretical papers is reviewed in the sections that follow to demonstrate the attributes of these two model types.

2.4.1 Representative agent type behavioural finance models

In representative agent type models, investors' behaviour is studied by looking at their various investment preferences. An investor's investment preference becomes an object by which the investor is assigned to a group for the purpose of the study. Sometimes the cognitive biases that influence investors' financial decision-making under different economic or financial states are also investigated using this type of model. All investors are treated as possessing a homogenous information set as well as behaving in similar ways with regard to their learning ability, correcting past mistakes, or even applying the same reasoning in predicting future outcomes of their investments. In addition, they possess the same payoffs for alternative investment choices. As Forbes (2009, p. 229) notes, "Representative agent type models are better at capturing the impact of biases in individual traders' utility behaviour but often do so at the expense of ignoring how these biases work themselves out in the process of trading an asset". Representative agent models are good at capturing investors' behaviour such as herding. I will review a few representative agent type theoretical models in the following sub-sections.

2.4.1.1 The Barberis, Shleifer, and Vishny (1998) model: model description

The Barberis, Shleifer and Vishny (1998) paper (henceforth BSV) entitled “A model of Investor Sentiment” presents a behavioural finance representative agent type model. The authors postulate a model in which representativeness heuristic and conservatism (a cognitive bias) influence an investor’s behaviour in forming beliefs about his investment decisions. In this model, when an investor observes two successive earning rises, the influence of the representativeness heuristic leads him to believe that he is in a trending (momentum) regime. On the other hand, conservatism leads him to believe that he is in a mean-reverting (reversal) regime when he observes an earnings rise followed immediately by an earnings fall. The model therefore proposes that an investor will always find himself in either of the two regimes. The regime in which the investor perceives himself to be depends on which of the two dominates. He believes that he understands the earnings cycle and knows which of the regimes dominates because he also believes that the two regimes rarely switch. So we can say that the BSV model essentially depicts two different models for the two regimes (or states).

The model posits that the investor does not perceive earnings as a true random walk process (according to the authors, the earnings-generating process in the true model is a random walk); rather he believes that the earnings-generating process switches between two states of the world. The investor believes that the two models generating earnings in each of the two states are different from one another. Both models (for the trending and mean-reverting regimes) exhibit the Markov process. This means that the change in earnings in period t is solely dependent on the change in earnings in the immediate past period $t - 1$. The difference between the trending and reversal models lies in their transition probabilities. A set of transition probabilities controls the switching from the trending regime to the mean-reverting regime and vice versa. The investor sees the switching process between the two different regimes as being controlled by an underlying regime-switching process. In the first regime, he believes that earnings are more likely to be mean-reverting, while in the second, earnings are likely to trend in the next time period. The investor also believes that next period earnings are more likely to mean-revert rather than trend: he assigns more ‘weight’ (probability value) to the mean-reverting model (model 1) than on the trending model (model 2). The transition probabilities between the two regimes and the statistical properties of the earnings process are fixed in the investor’s mind as a result of his prior experience and beliefs.

The investor observes his earnings each time and updates his beliefs about the earnings based on the information he received last period. Subsequently, he tries to update his model

in a Bayesian fashion, although his model is incorrect *ex post*. When there are two successive positive earnings surprises, the investor believes he is in the trending regime, while if a negative earnings surprise follows a positive earnings surprise; he raises the likelihood of being in a mean-reverting regime. Thus, he makes his forecast for future earnings.

One interesting thing about this model is that it does not make room for the investor to learn through time about the true earnings-generating process and therefore understand that the process is a random walk. Hence, his only task is to figure out which regime he is in in the current period and to use the appropriate model to forecast earnings. Something unusual about this particular characteristic of the model is that experience shows that human beings have the ability to learn and do make corrections from their past experience. So, one finds the idea that the investor never learns that he is using the wrong model somewhat far-fetched, and the assumption that one never learns seems a particularly odd for an academic rather than a professional to hold.

2.4.1.1.1 Evidence of underreaction and post-earnings announcement drift in the BSV model

BSV use their model to show how underreaction to earnings announcements occasioned by the influence of the representativeness heuristic on the investor could generate post-earnings announcement drift (a short-term continuation in stock price otherwise known as earnings momentum) following earnings announcement. The model shows that when a positive earnings surprise is followed by another positive surprise, the investor believes he is in the trending regime and raises the likelihood of model 2 prevailing, whereas if a positive earnings surprise is followed by a negative surprise he raises the likelihood that he is in the mean-reverting (reversal) regime and hence would use model 1 to forecast earnings. In the BSV model, underreaction is modelled to show that the average realised return following a positive shock to earnings is larger than the average realised return following a negative earnings shock. Underreaction occurs in this model as long as the investor, on average, believes that his earnings are generated by the mean-reverting model and places more weight on it than the trending model. Since the investor places more weight on the mean-reverting model than the trending model, he believes that the realised return following a positive earnings shock will be reversed in the next time period. However, if in reality earnings is a random walk process, then a positive earnings shock in this time period is equally likely to be followed by either a positive or a negative earnings shock in the next time period.

The model demonstrates that it can capture underreaction by showing that if the investor observes a positive earnings shock in this period, since he believes that the models rarely switch; he will believe that the mean-reverting model will generate earnings in the next time period. However, if the earnings shock turns out to be negative in the next time period, the realised returns will not be large, since this is what the investor had expected *ex ante*. On the contrary, however, if the earnings shock in the next period turns out positive, the realised returns are large and positive since this is unexpected. In a similar way, the average realised returns following a negative earning shock will be negative, hence the difference the two average realised returns is positive. This is consistent with the evidence of post-earnings announcement drift generated by investor underreaction.

In the BSV model, underreaction occurs insofar as the investor places, on average, more weight on model 1 (mean-reverting model) than in model 2 (trending model). The empirical implication of the BSV model is that underreaction occurs when the average realised stock return following a positive earnings shock is positive and higher than the average realised stock return (which is negative) following a negative earnings shock. The difference between the average realised stock returns following a positive earnings shock and the average realised stock returns following a negative earnings shock is positive. This is the underreaction effect, and this forms the basis of the authors' claim that post-earnings announcement drift is empirically evident in their model. In the BSV model, underreaction is seen as a consequence of the investor's conservative behaviour in adjusting his model when new earnings information is released.

Since in the BSV model the investor is supposedly rational and Bayesian, one would have thought that the investor would not expect that earnings are more likely to reverse every quarter. This is because in the real world, those indices by which companies' success are measured do not reverse so often, and so profitable (unprofitable) companies are more likely to remain profitable (unprofitable) at least for a few quarters or even years. Additionally, in the real world, as opposed to theoretical economic models, history does matter. It is therefore unlikely that this assumption made in the model can capture the true patterns that investors exhibit in real-world data.

2.4.1.2 The Rabin (2002b) model: model description

Rabin (2002b) models how believers in the 'law of small numbers' draw inferences from small samples of randomly distributed signals, believing that they are representative of the parent population from which they are drawn. The model is based on Tversky and Kahneman's (1971) work entitled "The Law of Small Numbers". In that work, Tversky and Kahneman show that people often exaggerate how representative a small sample is

compared with the parent population from which it is drawn. The Rabin model shows how people make this common error and how their decision-making process differs from a Bayesian inference process. It also shows that believers in the law of small numbers have the tendency to overinfer from a short sequence of independently identically distributed signals and to believe in a non-existent variation in the rate generating those signals. The rate here refers to a stationary probability by which each value of a signal is randomly generated. The model makes an economic application of the law of small numbers in three different situations to explain:

- Short-run underreaction by investors to recent corporate performance
- Medium-term overreaction by investors to recent corporate performance
- The tendency of investors to exaggerate the variation in skill among mutual-fund managers or analysts predicting earnings.

The investor's behaviour is influenced by psychological ideas such as the law of small numbers which presages the gambler's fallacy effect and overinference. The gambler's fallacy is an individual's mistaken belief that a second draw of a signal will be negatively correlated with the first draw. In the Rabin model, if the investor observes a sequence of binary signals of some underlying quality, for example, a series of good or bad investments by a mutual-fund manager (which the investor sees as a measure of the manager's level of competence) or a series of a firm's good or bad performance (e.g. quarterly earning outcomes), the investor infers the long-run prospects of the fund or the firm from the series. The model assumes that each value of this signal is generated randomly from a stationary probability. The model presents the investor as a Bayesian who holds correct probabilistic priors about the rate. However, while in reality the signals are generated by an independent identically distributed process, the investor believes that they are generated through random draws from an 'urn' which is sampled without replacement. An example is a draw from an urn of two signals, where the urn contains different proportions of values of the two signals corresponding to the rate. The example above captures belief in the 'law of small numbers', since the investor believes that the proportion of different signals must balance out to the population rate before any signals are observed. As the number of samples over some time period becomes large, the investor gets closer to being fully Bayesian. The smaller the sample, the more the person believes in the law of small numbers since for a one-off, event, the sample is also the population. So, for example, under the law of small numbers, if one rise in quarterly earnings has just occurred and has just been 'used up', there remains one less quarterly earnings rise to be observed in the future.

2.4.1.2.1 Evidence of underreaction and post-earnings announcement drift in the Rabin (2002b) model

The Rabin model demonstrates that it can capture an investor's underreaction to a series of a firm's quarterly earnings under the influence of the gambler's fallacy. Under the influence of gambler's fallacy, the investor underpredicts the chance of repetition of short 'strings' of performance signals in the model. This is because believers in the law of small numbers act as though short 'strings' or sub-sequences (with all the characteristics of the long sequences) are always embedded within the long sequences. This is a form of psychological bias known as the 'local representativeness bias, as reported by Bar-Hillel and Wagenaar (1991).

In the Rabin model, the investor underreacts when he observes a repetition of similar signals because he believes that the signal has less chance of occurring in this period. If the investor observes an earnings rise in this quarter, he underreacts if he observes another earnings rise in the next quarter. This underreaction stems from the fact that under the influence of gambler's fallacy, the investor expects an earnings fall in the next time period. It is interesting to note that with the arrival of the initial earnings signal, the belief of this investor (who believes in the law of small numbers) is the same as that of a Bayesian, since both possess the same probabilistic priors about quarterly earnings outcomes at that point in time. However, their belief diverges if this same signal reoccurs in the next time period. If subsequently the investor observes more of the same signal, he becomes more extreme in his predictions than a true Bayesian. Extreme prediction by the investor here marks his departure from the true Bayesian procedure of updating prior probabilities. This represents the effect of the gambler's fallacy on the investor, which is the source of the underreaction in the model. So we can say that when the investor observes a short sequence or streak of a firm's recent performance, he underreacts to it.

The way in which the Rabin model captures underreaction and overreaction is different from the way in which the BSV model captures them. In the BSV model, for instance, underreaction and overreaction are thought to occur as a result of two psychological influences – the conservatism bias and the representativeness heuristic – whereas in the Rabin model, underreaction and overreaction are caused by the gambler's fallacy. This characteristic of the Rabin model embeds a kind of an attractive parsimony into it. In the Rabin model, underreaction occurs in the short run while overreaction occurs in the medium to long run. In the model, both the underreaction and overreaction anomalies are connected by the investor's belief in the non-existent variation of the underlying rate generating the signals. The Rabin model believes that underreaction is most likely a natural outcome of the

gambler's fallacy, which comes as a result of a belief in the law of small numbers. The model demonstrates in this case how the bias influences an investor as he observes a single earnings-generating regime.

The Rabin model sees overreaction as a manifestation of a belief that there is more variation in intrinsic corporate performance than there actually is. In this way, investors would believe that there is more to learn than there really is from a time series of a company's performance indicators such as long sequences of quarterly earnings outcomes. When investors observe a long streak of the same signal, they overreact and exaggerate the likelihood that the observed signal is representative of the firm's long-term performance. This overreaction is a result of the influence of the gambler's fallacy on the investor when he observes a long sequence or streak of good or poor company performance.

Underreaction and overreaction occur in the Rabin model under the assumption that all investors live infinitely and invest randomly in one stock for four months. This process is repeated again, with the investors not re-investing in stocks in which they have invested earlier. The Rabin model then determines their belief about the distribution of the underlying quality of the stocks, where one of the two different signals a or b (positive and negative signals respectively) is either a positive or negative shock to a company's value. But in reality, these shocks do not predict more positive or negative shocks to the company's value, since the earnings-generating process is random.

For the investor observing the historical performance of a company, his average belief is a function of the company's recent earnings history. The investor determines his beliefs by considering all the possible historical performances of the company that he could observe in the next time period. The most recent company performance also falls within this historical data. The model shows that for short sequences of recent quarterly earnings performance, believers in the law of small numbers will underreact to a streak of one or two positive shocks to earnings and will generate momentum in price. On the other hand, long sequences of three or more positive earnings shocks in a row will cause investors to exaggerate the likelihood that the observed company is good. This is consistent with the finding of Barth, Elliott and Finn (1999).

Unlike the BSV model, the outcome of the Rabin model does not depend on the proportions of different signals that the investor observes. Rather, it depends on the actual sequence and sign of those signals. This fundamental property of the model marks an important divergence between the BSV and Rabin models. Moreover, it is intuitively more appealing to view the Rabin model as being more likely to capture true investor behaviour in real-world data. Therefore, as the model posits, it is more plausible that even rational investors are

prone to underreact to short sequences of signals, but are able to update their model as more information about the firm becomes available. In the real world, market participants update their forecasting models once they receive more value-relevant information about firms. Similarly, the ‘hot-hand fallacy’, which is related to the law of small numbers, may cause investors to overreact when they observe a long sequence of identical signals. This is because a long sequence, even when randomly generated, may induce a belief that the investor can separate stocks into ‘stars’ and ‘dogs’, even though, in fact, he cannot.

2.4.1.3 The Rabin and Vayanos (2010) model: model description

The Rabin and Vayanos (2010) model has a very simple structure. The model investor observes an earnings outcome, S_t , over periods, $t = 1, 2, \dots$ as shown by equation 2.1 below:

$$S_t = \theta_t + \epsilon_t \dots\dots\dots (2.1)$$

where θ_t is the state of the earnings outcome, be that a rising or falling trend in quarterly earnings and ϵ_t is a normally distributed shock with a mean of zero and constant variance i.e. $\epsilon_t \sim (0, \sigma_\epsilon^2)$. The most compelling insight from the model is the assumption that the signal concerning company value, θ_t , which the investor receives follows an auto-regressive process of the type shown by equation 2.2 below:

$$\theta_t = \rho\theta_{t-1} + (1 - \rho)(\mu + \eta_t) \dots\dots\dots (2.2)$$

where the value of ρ lies in the interval $0 < \rho < 1$, μ is the long-run mean of the signal and η_t is a specific temporal shock to that average value in time period t with variance σ_η^2 .

In this model setup, the ‘gambler’s fallacy’, a cognitive bias based on the ‘law of small numbers’, influences the investor to believe that the sample closely mimics the parent population from which it is drawn. This mistaken belief leads him to believe that the sequence $\{\epsilon_t\}_{t \geq 1}$ is not independently identically distributed, but rather exhibits reversals via a process of the form described by equation 2.3 below:

$$\epsilon_t = \omega_t - \alpha_\rho \sum_{k=0}^{\infty} \delta_\rho^k \epsilon_{t-1-k} \dots\dots\dots (2.3)$$

where the sequence $\{\omega_t\}_{t \geq 1}$ is independently identically distributed with a mean of zero and a constant variance σ_ω^2 , so $\omega_t \sim (0, \sigma_\omega^2)$, and $(\alpha_\rho, \delta_\rho)$ are model parameters defined on the interval $[0, 1]$, which itself is a function of the value taken by ρ . The primary difference between the ways in which α_ρ and δ_ρ influence the investor’s valuation expectations is that while α_ρ has a simple multiplicative effect in offsetting the current earnings surprises by the history of the past ones, δ_ρ enters as a polynomial δ_ρ^k where k denotes the number of

periods in the past when the particular earnings surprise being considered occurred (so for example a value of $\delta_\rho = 0.9$, an earnings surprise issued in the same quarter last year will take a reduced weighting δ_ρ^4 of 0.6561).

While the difference between the multiplicative weighting on past earnings surprises, α_ρ , and the exponentially declining weighting δ_ρ^k , may seem a trivial technical detail in the model, it underpins one of the model's central results. This is the ability of the model to capture two stock market phenomena often seen to stand in tension to each other. These are:

- In the short run, when k is low, the multiplication of α_ρ and δ_ρ^k ensure considerable power for the 'gambler's fallacy' that influences the mistaken belief that earnings surprises must be reversed in the future and this facilitates short-run momentum. Prior errors ϵ_{t-1} , offset the effect on the value of the current earnings surprise ω_t . This netting off is captured by the second term on the right-hand side of equation 2.3.
- In the long run, when k is large, the impact of past earnings surprises, $\epsilon_{t-1}, \epsilon_{t-2}, \dots, \epsilon_{t-k}$ on the current earnings surprise is minimised because higher powers of δ_ρ^k are so small in absolute value that they have minimal effect in offsetting the current earnings surprises embedded in ω_t . According to the Rabin and Vayanos model, it is in this latter phase of earnings dynamics that the influence of the 'gambler's fallacy' is curtailed and replaced by another cognitive bias termed the 'hot-hand fallacy'. The hot-hand fallacy influences people to believe that some stocks are inherently 'stars' or 'dogs'. It is this latter feat of recognition that presages the reversion / correction phase in stock market returns that serves to unwind the earlier momentum effects.

In accordance with the gambler's fallacy, the investor believes a high value of the disturbance ϵ in equation 2.3 above is likely to be reversed in the next time period. The parameter vector $(\alpha_\rho, \delta_\rho)$ captures this characteristic in the model. Much of the model's predictions concerning investors' evaluation of quarterly earnings changes derive from the interaction of α_ρ and δ_ρ and how that interaction characterises the misperception of the signal about the value that the quarterly earnings announcements send across. The degree to which shocks to earnings expectations are self-sustaining is clearly a function of the size of ϵ relative to the underlying signal regarding value θ , which is interpreted here as the most recent quarterly earnings announcement. A high ratio of signal θ_t , to noise ϵ_t in equation 2.1 above $\frac{\theta_t}{\epsilon_t}$ intensifies the investor's response to a quarterly earnings announcement.

The empirical implication of the Rabin and Vayanos model is that the model captures the impact of the behaviour of the investor when he observes short or long sequences of historical earnings surprises. According to the model, when the investor observes this sequence, he is likely to adjust his valuation model (caused by his misperception) in such a way that shows he is under the influence of either the gambler's fallacy or the hot-hand fallacy, depending on the length of the sequence. When the investor is under the influence of the gambler's fallacy, his investment decisions based on his model leads to earnings momentum in returns, whereas if he is under the influence of the hot-hand fallacy, that leads to long-term reversal in returns. Thus the resultant miss-specification of his model subsequently gives rise to incorrect forecasts.

2.4.2 Noise trader type behavioural finance models

Those behavioural finance models that consist of different types of investors are referred to as noise trader type models. In these models, investors are classified based on how sophisticated they are with respect to the collection and use of value-relevant information. Basically, there are two different types of investor – the informed (smart) and the uninformed (or not-so-smart or misinformed). Uninformed investors (traders) trade on noise and without regard for the fundamental values of the securities. They trade in this way because of the influence of certain cognitive biases and heuristics on their investment decision-making processes. When they trade in this manner, they make errors which lead to mispricing of securities in the financial markets. In this model, the role of the informed investors is to arbitrage away the trading errors created by uninformed investors. According to Forbes (2009, p.119 - 120), “noise is self-generated and creates its own space” and does not refer to other random events or shocks that cancel each other out over long periods of time¹⁸. Black (1986) observes that a large number of small pockets of noise are more effective than a small number of large events as a causal factor of market inefficiency. The author argues that noise somewhat causes markets to be inefficient and at same time makes it more difficult for arbitrageurs to take full advantage of such inefficiencies. De Long *et al*'s (1990b) model shows that the unpredictability of noise traders' beliefs creates risk in asset prices and thus arbitrageurs are not willing to trade against such beliefs. Hence noise traders “create their own space” in the markets. This means that prices of assets can move away significantly from the fundamental value (because arbitrageurs are unable to curtail this divergence) even in the absence of fundamental risks. Therefore, for noise trader models to perform well, a good proportion of the ‘noise’ modelled must come from within and must be self-generated. This means that the types of ‘noise’ in this model must not cancel each other

¹⁸ See also De Long *et al* (1990b).

out in different trading sessions. This sort of 'systemic risk' which trading does not eliminate, but may indeed magnify, was perhaps at the heart of the recent financial crisis. I review a few theoretical noise trader type behavioural finance models in the following sub-sections.

2.4.2.1 The Hong and Stein (1999) model: model description

The Hong and Stein (1999) model provides a noise trader type model that comprises two types of investor. The authors term these traders 'newswatchers' and 'momentum' traders. Both types of trader are rational but suffer from limited or bounded rationality. Bounded rationality implies that each type of trader is only able to process a sub-set of information available to them (and not the full set of information). The newswatchers trade on their private information about firm fundamentals. At the same time, each individual newswatcher is unable to extract information from other newswatchers' prices. The newswatchers make their forecasts based on private signals about the firms' future fundamentals that they receive but do not condition their forecast on current or past price changes. They receive these signals in a clearly defined 'rotation', as each valuation signal is released to its receiver. On the other hand, momentum traders condition their forecasts only on past price changes. For the momentum traders, their forecasts must be simple univariate models conditioned on price.

If the actions of the newswatchers cause security prices to diffuse slowly across investors in security markets, prices will underreact in the short run. The momentum traders then trade on the trending prices resulting from the underreaction effect. When newswatchers are active, but not momentum traders, the price moves and adjusts slowly to private information – this is the source of underreaction in the model. The price moves and adjusts slowly as a result of the rate of information flow. It is appealing to think that momentum traders will arbitrage away all the mispricing opportunities created by the newswatchers, thereby pushing the market back to rational equilibrium. However, since momentum traders are limited to simple and uncomplicated forecasting models, this does not happen. They simply do not possess the expertise to exploit all the available mispricing. Rather, as momentum traders continue to arbitrage away the mispricing caused by investors' underreaction to price, the price moves further away from the fundamental value, leading to long-run reversal. The Hong and Stein (1999) model assumes that all the newswatchers have constant absolute risk aversion utility with the same risk-aversion parameter and hold their security until the terminal date. In contrast, the momentum trader does not hold the security until liquidation; rather, as a short-term trader, he holds it for j periods. This becomes his target holding period. Hence, the contrasting behaviour of both types of trader feeds into the continuous cycle of mispricing the security. The model also assumes that the momentum

trader looks at past price data in determining whether to follow the price in making his investment decisions. The authors demonstrate the behaviour of the momentum trader by illustrating how the trader at time t must base his decision to trade on past price changes over time period intervals of say between $t - 2$ and $t - 1$.

Hong and Stein (1999) show that the momentum trader's attempt to take advantage of the resulting underreaction caused by newswatchers leads to further mispricing. The price of stock, which hitherto has been moving according to the forecast based on the stock's fundamentals, is accelerated by the actions of the newswatchers, who by jumping in on the existing price trends cause a price overreaction in the long run. The model shows that a momentum trader's trading strategy earns the bulk of its profit early in the cycle; that is, shortly after substantial news arrives with the newswatchers entering the market. The momentum traders, however, lose money later in the trading cycle, by which time prices are believed to have overshot the long-run equilibrium values and the correction phase has set in. One interesting aspect of the model is that although the fundamental cause of underreaction and overreaction anomalies are not thought to be based on individually held psychological biases, the model is able to capture both underreaction and overreaction anomalies through the interactive actions of the two types of trader. In this model, the emphasis is on how the heterogeneous agents interact with each other and the resultant underreaction and overreaction anomalies.

2.4.2.1.1 Evidence of underreaction and overreaction in the HS model

In the Hong and Stein (1999) model, momentum traders earn abnormal returns as a result of mispricing caused by the activities of the newswatchers. This mispricing stems from the fact that newswatchers observe only private information and do not condition their models on current or historical prices. This model attempts to capture the effect of heterogeneous agents in the market and to show how their investment decision-making causes mispricing in the market. Essentially, the model shows the actions of two different types of agent in the market and how they process their information sub-sets. However, both types of agent are not fully rational. They suffer limitations from bounded rationality, in the sense that they are only able to use a certain sub-set of information available to them. In the model, momentum traders use past prices while newswatchers use certain chosen fragmentary elements of value to predict firms' future fundamental value.

In the model, when only the newswatchers are active, prices adjust slowly to new information and this causes underreaction. This follows from the fact that newswatchers by their nature are unable to extract information from the prices of other newswatchers.

Furthermore, there is a gradual diffusion of private information about the price across investors in the markets. The model shows that this slow diffusion of information across the market creates momentum in price. Subsequently, there is a positive autocorrelation of returns in short horizons. However, when the momentum traders enter the market, the model shows that because they condition on current and past prices, they partly exploit any mispricing opportunities caused by underreaction left behind by the newswatchers. The rate of information flow across the market in the model has another implication for the cross-section of stock returns. The slow diffusion of information in the model causes higher short-run return corrections. This makes stocks attractive to momentum traders, but at the same time causes pronounced overshooting of stocks from fundamental values, which leads to stronger reversals in the long run. The action of the momentum traders does not move the market back to the fundamental value, because their actions lead to price movements being accelerated and eventually cause overreaction to any news. So in the model, momentum traders may move the price back to value and even far beyond the true value. This could motivate a 'correction phase' following the overshooting of a reasonable long-run price. The underreaction and overreaction anomalies occur at different points in the cycle and are set off by the activities of newswatchers and momentum traders. Unlike in the BSV model, they do not occur in two different regimes or cycles. This implies that the stocks that are more prone to momentum are the same stocks that will face more severe reversals later on in the future.

2.4.2.2 The Daniel, Hirshleifer, and Subrahmanyam (1998) model: model description

Daniel, Hirshleifer and Subrahmanyam (1998) (henceforth DHS) propose an alternative theory of security market underreaction and overreaction which centres around two cognitive biases. The biases are investors' overconfidence about the precision of the private information they receive and the self-attribution bias. Overconfidence is the tendency of individuals to overestimate their own knowledge, underestimate risk, and exaggerate their abilities. On the other hand, self-attribution bias is the tendency for individuals to attribute their success to their own ability and failure to external factors. The authors show that overconfidence could lead to long-run reversals and excess volatility, when the actions of managers of a particular firm are correlated with the mispricing of the firm's stock or with public event-based predictability of returns. In addition, they show that the self-attribution bias results in positive short-lag autocorrelation; that is, momentum and short-run earnings drift (post-earnings announcement drift). The emergence of momentum in the model is a result of the self-attribution bias causing asymmetric shifts in investors' confidence in response to the outcomes of their investments. The central theme of the DHS model is that stock market prices overreact to private information signals and underreact to public signals.

The DHS (1998) model posits that individuals attribute events which confirm the validity of their actions to their own 'high' ability, while they attribute any refutation to sabotage or external noise. DHS theory asserts that the investor's confidence rises if the public information he receives confirms his private information signal, but his confidence does not fall commensurately if the public information contradicts his private information. The authors also assume that investors view themselves as more able to value securities better than they actually are and underestimate the magnitude of their forecast errors. The model assumes that the investor is quasi-rational, in that, although he is Bayesian, he incorrectly overestimates the precision of his private information. He is also biased in the way in which he updates this information. He knows the private signal but is confused about its value in predicting earnings. Investors tend to 'overweight' confirmations from public signals and at same time 'underweight' contradictions in their own revision processes. In the model, the investor is only overconfident about the private signals, and this behaviour captures both the underreaction and overreaction anomalies. This is a model of an 'outcome-dependent confidence'.

2.4.2.2.1 Evidence of underreaction and overreaction in the DHS model

The DHS model believes that investors underreact to each firm's public information in a manner which is time inconsistent. The self-attribution bias causes investors with confirming public information (in accord with their private signals) to overreact, and their continuing overreaction will cause momentum in the short term. However, if the overreaction continues, there is a long-term reversal or a correction phase. In the long run, the correction phase pushes the security price back to the fundamental as further public information slowly filters into the market. Thus, the self-attribution bias leads to momentum in the short run and long-term reversal in securities prices in the long run.

The model considers the fact that the investor's confidence varies over time and this causes continuous overreaction to private signals over the time horizon. In the DHS model, the investor's overconfidence in the private signal causes the date 1 stock price to overreact to the new private information. However, at date 2, when public information arrives, the inefficient deviation of price before this date due to excessive reliance on the private signal is partially corrected on average (at least on average). This correction continues when further public information arrives at a future date; say date 3. The resulting overreaction and correction phase imply that the covariance between date 1's price change and date 2's price change is negative. Although there is a partial correction of the private signal overreaction phase by the arrival of the public signal on date 2, full correction of this overreaction occurs on date 3 with the arrival of another public signal. The price change reversal occurs as a

result of the arrival of public information on date 2 which continues and ends on date 3. The price changes in the two correction phases are positively correlated. In the DHS model, it is important that an earnings announcement or another 'price trigger' event is 'selected', in the sense that it signals the difference between what managers and the outside investors know.

2.4.2.3 Other noise trader type models

There are other noise trader type models of underreaction and overreaction in the behavioural finance literature. Some of the earliest and most prominent research work includes Stein (1987), Shleifer and Summers (1990), and De Long, Shleifer, Summers, and Waldmann (1990a, 1990b). De Long *et al* (1990a) model comprises three types of investor: positive feedback traders, informed rational traders, and passive investors. The total number of the second and third type of investors is kept constant in the model as a control measure. The model shows that early positive feedback trading from rational investors could trigger a herding effect from 'noise' or irrational traders. This in turn could lead to an increase in the volatility of the fundamental value of the asset. A positive feedback trading strategy is one that buys when prices rise and sells when prices fall. The model shows that in a situation where positive feedback trading triggers the herding effect; there is a positive correlation of asset returns in the short run and an overreaction of asset prices to news leading to negative correlation in assets returns in the long run. As this process of correction continues, prices eventually return to their fundamental values. De Long *et al* (1990b) create a model which shows how the activities of irrational noise traders (not fully rational investors) with erroneous beliefs about prices could lead to more risk in the price of the asset. This increased risk could lead rational investors to reduce their activities, since the price will diverge from the fundamental values even when there is no accompanying fundamental risk.

Stein's (1987) model shows that even though speculators in the market are all rational investors, introducing more speculators after the initial ones have arrived can change the information content of prices. Stein examines the impact of a 'staggered execution' of trades and its impact upon price formation. The arrival of late investors introduces an externality into the price for those traders who are already in the market and who make inferences based on price. The entry of new speculators lowers the informativeness of the price, and this can lead to price destabilisation and welfare reduction.

Similarly, Shleifer and Summers (1990) provide a noise trader type model which comprises two types of investor. The first set of investors is not fully rational, whereas the second set is fully rational. The model posits that investors who are not fully rational are influenced by sentiments (or their beliefs) when demanding risky assets. The actions of the not fully

rational investors create inefficiency in price, but because this is risky, fully rational investors are not able to fully arbitrage away this mispricing.

One common argument amongst the noise trader type models is the belief that the security markets comprise more than one type of investor or trader. They believe that the activities of irrational or not fully rational or 'noise' investors create inefficiency in prices which then leads to short-run momentum and a subsequent long-run reversal in asset returns. There is a kind of consensus amongst the proponents of these models that the heterogeneous noise trader type models are in many ways superior to the efficient market models. This is because in the real world, investors are likely to hold different information sets, and their abilities to analyse and understand the market will also be different.

2.5 Information uncertainty

Several studies in the literature document the effects and influence of information uncertainty on both stock returns and expected stock returns. Others examine the influence of information uncertainty on both earnings and price momentum. The question remains as to whether information uncertainty exacerbates the earnings and price momentum anomalies, and to what extent that influence might be.

Information plays a very important and central role in the financial markets. Most of the economic models base their propositions on the rationality of the economic agent, who is expected to possess every useful piece of information about the market through which he can make informed choices. The asset pricing models such as Sharpe's (1964) Capital Asset Pricing Model (CAPM), Merton's (1973) Inter-temporal Capital Asset Pricing Model (ICAPM), and Ross's (1976a) Arbitrage Pricing Theory (APT) are constructed based on a perfect and frictionless market where information flow is efficient and available to all market participants.

Zhang (2006a) defines information uncertainty as the level of ambiguity associated in ascertaining a firm's fundamentals at a point in time when new information about the firm is released. Information uncertainty, as used here, does not mean the same as information asymmetry, as the latter denotes the case where some market participants have more information about a firm's fundamental values than others. The author documents that ambiguity with respect to the implications of new information about a firm most likely stems from two different sources: the volatility of a firm's underlying fundamentals and the poor quality of information or 'noise'. The level of information uncertainty in a firm's fundamental is measured by the variance of the observed signal of the firm's fundamental and the quality of the information. In other words, the uncertainty about a firm's underlying fundamental value

is measured as the volatility of the firm's underlying fundamentals, such as dividends, cash-flows, earnings outcomes and/or the variance of the noise accompanying the new information. Jiang, Lee, and Zhang (2005, p.185) define information uncertainty as "the precision with which firm value can be estimated by knowledgeable investors at a reasonable cost". The authors define high information uncertainty firms as those firms whose expected fundamental values can be predicted with less certainty. This could be a result of the nature of the business in which the firms are engaged or the environment in which they operate. According to the authors, high information uncertainty firms are usually firms associated with a higher cost of acquiring information and the forecasts of their fundamentals are more likely to be less reliable and more volatile.

2.5.1 Price Momentum, post-earnings announcement drift and information uncertainty

Most studies in the literature agree that high information uncertainty exacerbates the post-earnings announcement drift anomaly when conditioned on the nature of earnings news. Zhang (2006a, 2006b) is amongst the pioneering studies in literature to document the influence of different levels of information uncertainty on both stock market returns and analysts' forecast behaviour. Other studies such as Chen and Zhao (2012), Francis *et al* (2007), Gerard (2012), Gyamfi-Yeboah *et al* (2012), and Jiang, Lee, and Zhang (2005) also document that information uncertainty exacerbates investor underreaction to earnings announcements.

We know from prior studies that investors underreact to new information about firms' fundamentals such as earnings announcements, dividend initiation or omission, cash-flow, etc. The common argument is that if investors and other market participants underreact to new information, such as a quarterly earnings announcement, the effect is post-earnings announcement drift in stock prices. However, in a moment of uncertainty regarding a firm's fundamental, considerable levels of information uncertainties will most likely cause investors to underreact even more to the new information. Jiang, Lee, and Zhang (2005), in their study on information uncertainty and the cross-section of stock returns, document that, on average, unconditional high information uncertainty firms have lower future stock returns. The authors also report that conditional information uncertainty exacerbates earnings and price momentum effects in firms with high levels of uncertainty, and this leads to strong drifts in price. They claim that high information uncertainty has a dual effect on investors by driving up their confidence and at the same time limiting rational arbitrage among knowledgeable investors. In other words, it appears there is an interaction effect between information uncertainty and momentum effects that generates higher future stock returns for firms with high information uncertainty regarding their future fundamentals. It is not difficult to

understand why high information uncertainty will limit rational arbitrage, since high information uncertainty will drive up the risk-premia demanded by arbitragers. Furthermore, Jiang *et al* (2005) posit that since classical asset pricing models propose that idiosyncratic variations in firms' fundamentals should not explain the cross-section of returns, it is therefore puzzling that high information uncertainty proxies conditioned on the nature of news are able to predict future stock returns. The ability of information uncertainty conditioned on the nature of news to explain returns is puzzling, because if variations in a firm's fundamental uncertainty are not systematic, it should not be able to explain a cross-section of returns in a well-diversified portfolio.

Zhang (2006a, 2006b) investigates the roles of information uncertainty in price continuation anomalies, such as investors' and analysts' underreaction to analyst forecast revisions. Investor underreaction to the earnings announcement manifests in stock prices by pushing prices in the direction of recent quarterly earnings surprises in the period following the earnings announcement. Consequent upon this, Zhang (2006a) observes that when price drift is attributed to behavioural biases, the drift becomes more intense if there is high uncertainty about the firm's fundamentals. The direction of this drift will depend on the nature of news – price will drift upwards (downwards) for good (bad) news firms. The author uses information uncertainty proxies such as firm size, firm age, analyst coverage of firms, dispersion in analyst forecasts, return volatility, and cash-flow volatility to show that high (low) information uncertainty leads to large (small) drift in stock returns following good (bad) news in a way that suggests that information uncertainty delays the flow of information into stock prices. The author documents that evidence from his study shows that on the arrival of new information, low information uncertainty stocks do not draw any dramatic reaction from the market and there is therefore little news-based return predictability. He also documents that price momentum and other trading strategies that buy good-news stocks and sell bad-news stocks perform better when conditioned on higher information uncertainty stocks. This position is consistent with the findings reported in Jiang, Lee, and Zhang (2005). The authors find that there is no significant relation between information uncertainty proxies, such as cash-flow and stock volatility, and unconditional expected stock returns. This finding suggests that variations in information uncertainty proxies themselves are only able to explain returns when conditional on the nature of earnings news. Again this supports the behavioural argument that information uncertainty only magnifies the impact of earnings news on post-earnings announcement drift.

Zhang (2006b) investigates how information uncertainty and cognitive biases influence a sell-side analyst's recommended decision. The author shows that high information uncertainty predicts positive (negative) forecast errors and future forecast revisions following

good (bad) news. This suggests that information uncertainty delays the flow of ambiguous information into analyst forecasts. The author also shows that information uncertainty has opposite effects on good and bad news firms. This anomalous behaviour is consistent with the hypothesis that analysts underreact more strongly to good and bad earnings news in the presence of high uncertainty. He finds that the effect of information uncertainty on analyst behaviour is stronger following bad news than following good news. Therefore, analysts are more prone to apply a harsher downward revision to bad news firms and a less generous upward revision to firms with commensurate good news. This behaviour has a link to a psychological principle known as loss-aversion, which suggests that individuals attach more weight to losses than they do to gains of equal magnitude (see Kahneman and Tversky (1984), Tversky and Kahneman (1991)). Another interesting finding of the paper is that as the forecast horizon decreases and more information becomes available, analysts' forecasts tend to improve (worsen) for good-news (bad-news) firms.

Francis, LaFond, Olsson, and Schipper (2007) examine the role of information uncertainty in explaining the properties and returns of a post-earnings announcement drift trading strategy. The authors find that unexpected earnings components of high information uncertainty firms show no dramatic market reactions. High unexpected earning portfolios are found to contain more high uncertainty stocks than low unexpected earning portfolios. Within portfolios of high unexpected earnings stocks, high uncertainty stocks earn larger abnormal returns than low uncertainty stocks. This shows that high information uncertainty when conditioned on good news (high unexpected earnings) leads to a strong upwards drift in returns. This finding is consistent with the findings of Jiang *et al* (2005), who report that the effects of price and earnings momentum are much stronger in high uncertainty than low uncertainty stocks.

Price, Gatzlaff, and Sirmans (2012) examine the effects of information uncertainty on the post-earnings announcement drift anomaly for real estate investment trusts (REIT). We expect the earnings announcement to be a more certain signal for REITs due to the presence of a parallel (private) asset market (which implies an additional source of information for REITS investors) and therefore should imply less uncertainty and ultimately lower drifts for REITs. But contrary to this logic, the authors find that the size of drift is larger for REITs than in ordinary common stock (non-REITs). The authors conclude that despite the fact that there exists a parallel (private) asset market which provides a rich information environment for the investors, the flow of information from private market to the public market seems to be delayed. The authors attribute this to information uncertainty, which they argue inhibits the rate of flow of publicly announced earnings signals into stock prices in a timely manner.

2.6 Summary

The predictability of returns around earnings announcements constitutes a very interesting area of research in the finance literature. The reason for this is that first, if the arguments of the efficient market hypothesis are valid, returns should not be predictable; second, the persistence of such predictability could imply that they might be useful trading strategies that might be profitable; and third the quest to understand the true phenomenon that causes the predictability of returns around this important firm event. These are some of the major reasons that drive research on the predictability of returns around earnings announcement.

Earnings and price momentum are the two major return anomalies that are predictable. Although both anomalies show an upwards drift in the stock prices, the processes that initiate them are separate from each other. Research shows that while the earnings surprise measure explains earnings momentum (post-earnings announcement drift) in returns, historical price data explains the price momentum anomaly. However, there remains a relation between the two anomalies, in that the systematic component of the earnings momentum subsumes the price momentum anomaly in a multivariate regression analysis¹⁹. Furthermore, trading strategies based on both anomalies are separately profitable, again suggesting that although both anomalies are related, they capture two different kinds of reaction in the market.

A number of theoretical behavioural finance models propose theories for the study of momentum anomalies. The fundamental similarity between these models lies in their belief that momentum occurs as a result of influence of certain cognitive biases and/or heuristics on investors' decision-making processes. Another belief that is common amongst these models is that market participants do not always hold the same information set and do not possess the same level of expertise in the collection, processing, and use of value-relevant information. These theoretical models can be broadly divided into representative agent and noise trader type models. The underlying difference between the two groups of models is that representative agent models study the investor through a representative 'everyman' kind of investor, while noise trader models study investors as a heterogeneous group with different levels of information processing powers. This study adopts the representative agent type model for the reasons given previously.

The study of earnings momentum generally centres around the impact of new earnings information on price. This information comes in the form of innovation in the most current earnings announcement. The innovation in earnings is the difference between the actual

¹⁹ See Chordia and Shivakumar (2006).

earnings outcome and the expected earnings. So, innovation to earnings can be seen as the 'shock' to the announced earnings. Various earnings momentum models adopt diverse methods to measure earnings innovation. The common name adopted in behavioural finance literature for this innovation is 'earnings surprise'. The most popular measures of earnings surprise in literature are the standardised unexpected earnings and analyst forecast revision. In this study, I adopt a new metric to measure the impact of earnings innovation on price. The new metric is the sequences or streaks of earnings surprises calculated over many quarters. Here, the new information that comes with the earnings announcement is either confirmation or termination of the lengthening streak of quarterly earnings surprises. The change in quarterly earnings or the earnings surprise is used to proxy the change in investors' expectations of earnings at the time when earnings are announced. Moreover, from the behavioural finance point of view, it is during the processing of the information contained in the earnings surprise that investors become vulnerable to the influence of biases and heuristics. My thesis focuses on how sequences or streaks of earnings surprise impact on stock returns after the earnings announcement. The Rabin (2002b) and BSV (1998) models propose that under the influence of different biases and heuristics, investors observing sequences of earnings surprises will produce incorrect earnings forecasts with their models. This will subsequently result in the abnormal behaviour of stock prices.

Closely related literature is reviewed in chapters 4 and 5 and the hypotheses follow directly from them.

Chapter 3

Data and methodology

3.1 Introduction and data description

The main objective of this chapter is twofold: the first part discusses the nature and sources of various data used in this research and the second part of the chapter is devoted to the various methods employed in carrying out the empirical analyses. The quality of empirical research very much depends on the dataset used and the methods followed at the analysis stage. It is also equally important to ensure that variables and proxies used in research are measured in a way that will minimise error. For this reason, I use the S&P500 sample frame, which is likely to comprise high quality data with few reporting errors.

This chapter introduces the sources of data used in this research work. It also describes the data collection process and the ‘make-up’ of any individual piece of data used in this investigation. Although the data collected are secondary data, nevertheless, the majority of them are not used in the exact form in which they were initially collected. Some of the data have undergone several transformations to obtain the required proxies from them. Once a company enters the S&P500 index, I do not remove it from my dataset even if it exits the index before the end of my sample period. In this way, I try as much as possible to reduce the incidence of survivorship bias²⁰. I have a total of 837 constituent companies in my S&P500 index over the sample period from January 1991 to December 2006. This reflects the turnover and attrition of the 500 companies present in the index in any particular month.

The second objective of this chapter is to describe the main methodology applied in this research work. For methods that are not common to the two major empirical chapters of this study, their description will be in their respective empirical chapters. Here I present the main list of methods of analysis that are followed in both chapters 4 and 5.

3.2 Description of data sources

The sample data used in the research work is collected from various data sources and databases, which include Standard & Poor’s Financial Services LLC, The Institutional Brokers Estimate System (I/B/E/S), Thomson financial DataStream, and the Professor Kenneth French Data library webpage. The quarterly earnings-per-share announcement dates, company market capitalisation, book value of equity, weekly return on the S&P500 index, company cash-flow from operations, daily and monthly stock price data are collected from DataStream. Additionally, the quarterly earnings-per-share, consensus analysts’

²⁰ See Brown *et al* (1992).

forecast of earnings-per-share, analysts' coverage of companies, analysts' forecast revision, and consensus analysts' forecast dispersion are collected from the Institutional Brokers Estimate System database. The index services of Standard & Poor's Financial Services LLC provides the dates when companies were added and/or deleted from the S&P500 index. Finally, the Fama-French size and book-to-market benchmark portfolios and factors are collected from Professor Kenneth French's online data library webpage.

3.3 Methodology

In this section I discuss methods used to measure variables and proxies used for analysis in the empirical chapters. However, the sections that follow discuss the measurement of proxies and variables common to both empirical chapters. Here, I discuss in more detail the main measures and proxies that I set out to use in my analyses:

- The first among the measures is the sequences of changes in annualised quarterly earnings over a period of twelve quarters. This measure captures the various levels of investor behaviour in response to various lengths of rising or falling sequences or streaks of earnings surprises over twelve quarters. This test allows me to examine how belief in the law of small numbers, as proposed by Rabin (2002b), might influence investors' decisions following quarterly earnings announcements. The test shows the association between the 'streaks' of changes in investors' earnings growth expectations, over many quarters, and the subsequent market response. The sequences of quarterly earnings changes are calculated using the annualised quarterly earnings change normalised by prior year-end stock price. This price is the stock price on the last day of quarter t-4. The sequence of quarterly EPS change metric is used in chapter 4.
- Second, market response to streaks of changes in investors' earnings expectations around quarterly earnings announcement dates are examined in chapter 5. Again, I measure the quarterly earnings surprise (ESURP) by subtracting the most recent consensus analyst forecast from the actual quarterly earnings in the relevant quarter. This is then normalised by the prior year end stock price. Again, the year-end stock price is the stock price on the last day of quarter t-4. I use this metric to examine whether the stock prices are following the same direction as the streaks of ESURP in terms of both their sign and intensity. This is done by examining the response of three-day buy-and-hold abnormal returns to the streaks of ESURP three days around the earnings announcement. The holding period begins a day prior to the earnings announcement date and

ends a day after. It is believed that market reaction towards quarterly earnings announcements is most intense in this period, as market participants are working out the implication of earnings information for stock price. Jegadeesh and Titman (1993) document that analysing stock returns within a short window around the earnings announcement date (a period when key firm-specific information is being disseminated) ensures that they have a sharp test which is able to assess the potential biases in market expectations. Bernard and Thomas (1989, 1990), Freeman and Tse (1989), and Jegadeesh and Titman (1993) also employ a three-day holding period around the earnings announcement date to test for post-earnings announcement drift. This focuses interest in the period during which the market incorporates new earnings information.

- Third, previous work in the literature, notably Zhang (2006a), posits that when investors underreact to earnings announcements from high information uncertainty firms, this induces larger price drift in their stocks. In chapter 5, I introduce Zhang's (2006a) information uncertainty proxies and variables to investigate whether they will produce larger post-earnings announcement drift in the presence of streaks of quarterly earnings surprises of my S&P500 sample companies. I also test whether individual information uncertainty proxies have a significant univariate impact on post-earnings announcement drift.

3.4 Variables and proxies: definition and measurement

I measure investors' expectations in two different ways. Investors' expectations are measured first using earnings growth, $(E_t - E_{t-1})$ and second using expected earnings from consensus analysts' forecasts of quarterly earnings. These two are used to construct two different earnings surprise metrics which are used to investigate a representative investor's response to earnings realisations. I also use analysts' consensus forecast revisions, which is an alternative earnings surprise metric used to measure change in investors' earnings expectations, to check for the robustness of the results from the first two earnings surprise metrics.

3.4.1 Earnings announcement and the 'earnings surprise' metrics

There is a vast body of literature showing that the market responds to earnings surprises in a manner that suggests incomplete, or delayed, flows of information into stock prices. Previous research works, for example those of Ball and Brown (1968), Foster, Olsen and Shevlin (1984), and Bernard and Thomas (1989, 1990), show that the market response is more

intense when the earnings surprise is negative (so, bad news travels quickly). It is not surprising that the market seems to respond more strongly to the news of those firms that are making losses or those to which earnings are declining. Obviously loss-making firms are more likely to declare bankruptcy in the long run than profit-making firms.

There are different schools of thought on the reason(s) for the delayed response of stocks prices to the earnings news. Bernard and Thomas (1989) document that there are different competing arguments amongst researchers as to why stock prices continue to drift long after earnings announcement dates. First, some argue that the delay could be because investors are unable to assimilate the information contained in the earnings news quickly. Second, others argue that the cost of implementing a certain trading strategy could be responsible. The third group argues that the reason could be because the opportunity cost of immediate exploitation of the earnings information exceeds the gains for a greater number of traders. Furthermore, others argue that the benchmark models used in calculating abnormal returns, such as the Capital Asset Pricing model (CAPM), are either incomplete or miss-estimated and as a result, realised returns are not fully adjusted for risk. Jacob, Lys, and Sabino (2000) argue that post-earnings announcement drift is a result of researchers over-differencing an already stationary time series. Over-differencing of a time series occurs when the original time series which is already stationary is inadvertently differenced in order to achieve stationarity. The authors document evidence that shows that post-earnings announcement drift in their sample is driven by a sub-set of firms where over-differencing of quarterly earnings has occurred while estimating earnings surprise. However, the authors do not explain why Freeman and Tse (1989) find post-earnings announcement drift in stocks using the actual earnings and analysts' forecast measure. The finding of Freeman and Tse therefore refutes Jacob *et al* (2000) argument and shows that the presence of post-earnings announcement drifts in stocks cannot be attributed to methodological flaws.

I employ different tests to examine how investors respond to sequences or streaks of changes in expected earnings over different horizons. I ask if investors monitoring firms' earnings are just interested in the raw changes in quarterly earnings, or if they are more interested in the consistency of sequences (streaks) of such changes over many quarters (between two and twelve quarters). In the first empirical analysis (chapter 4), I create sequences of each company's quarterly earnings changes using the company's historical time series of quarterly earnings. This measure shows if a company's quarterly earnings change is consistently rising or declining across twelve quarters. I examine the intensity or the strength of this continuation/reversal in quarterly earnings and the investors' response to them. Furthermore, I use the different sequence lengths to examine the behaviour of investors at different points as the sequence intensifies or resolves. I show how 'surprised'

the investor is when companies consistently post positive or negative earnings changes over many quarters. I also show investors' response to companies that consistently post declining earnings over many quarters. I compare this with investors' response to companies that post positive earnings over the same length of time. For companies which consistently post declining or negative earnings, I examine if investors demand a premium to invest in such firms or whether companies that post consistently strong earnings performances enjoy discounts to their cost of capital.

In chapter 5, I test the investors' response to changes in earnings expectations around earnings announcement dates using streaks of quarterly earnings surprises (ESURP) to capture this change. I construct the quarterly earnings surprise metric by subtracting the most recent consensus analyst forecast of earnings from the actual quarterly earnings in the most recent quarter. This is then normalised using the prior year end stock price. Streaks of quarterly earnings surprises are constructed from the quarterly earnings surprise metric (ESURP) in the most recent quarter. A streak of quarterly earnings surprises occurs when there are rising, or declining, quarterly earnings surprises for at least two consecutive quarters. A streak of rising (declining) quarterly earnings is denoted as positive (negative) streak. I demonstrate the investor's response to streaks of good quarterly earnings news (when there is a growing ESURP for at least two consecutive quarters) and to streaks of bad quarterly earnings news (when there is a declining ESURP for a minimum of two consecutive quarters). The strength of price response to the streak lengths demonstrates the level of surprise that investors have towards the confirmation or termination of a growing streak at earnings announcement. I also introduce Zhang's (2006a, 2006b) information uncertainty proxies to examine the impact that the uncertainty generated by the firms' underlying fundamentals would have on the post-earnings announcement drift within a three-day window around the earnings announcement date. It has been argued severally in prior studies that some of the post-earnings announcement drift could be explained by the volatility of a firm's valuation fundamentals²¹. Information uncertainty consists of two components – the volatility of a firm's underlying fundamentals and poor information (Zhang (2006a)).

I use the firms' earnings announcement dates to determine my cut-off dates for the calculation of the earnings surprise metric (ESURP) and determine my sample firms' estimation and event windows around which performance is evaluated. I also use the monthly consensus analyst forecast of earnings from the I/B/E/S database and the actual

²¹ See Cao and Narayanamoorthy (2012).

quarterly earnings announcement date to determine the change in earnings expectations for each monthly period in my sample.

3.4.2 Sequences of quarterly earnings-per-share changes

I measure quarterly earnings-per-share change following the Chan *et al* (2004) procedure for measuring performance proxies. I use quarterly earnings per share excluding interest and extra-ordinary items for my computations. This earnings-per-share type excludes special items or one-time large items which may otherwise affect the true size of realised earnings per share. I use an annually smoothed quarterly earnings (an annualised quarterly earnings change of four rolling quarters) metric of the form in equation 3.1 below to calculate change in quarterly earnings:

$$\Delta Q_{it} = [(Q_{it} + Q_{it-1} + Q_{it-2} + Q_{it-3}) - (Q_{it-4} + Q_{it-5} + Q_{it-6} + Q_{it-7})] \dots\dots\dots (3.1)$$

where (Q_{it}) is the earnings per share for company i in the most recent quarter (i.e. quarter t), while Q_{it-k} are the lagged values of Q_{it} from periods $t - 1$ and $t - 7$. I adopt this method to measure the quarterly earnings change to avoid seasonality in the time series of the data. By using this metric, it is assumed here that investors usually compare growth in earnings-per-share across analogous quarters in a four-quarter period. While I exclude a few extremely large changes in earnings per share which could be attributed to errors in the I/B/E/S database, I do not generally winsorise the data sample, because I assume S&P500 constituents usually have accurate reports of their earnings and prices.

To ensure that the quarterly earnings-per-share change for all companies are comparable to each other, I deflate the quarterly change in earnings-per-share equation with the prior stock price P_{t-4} (which is the stock price on the last day of the immediate past analogous quarter) from four calendar quarters prior to the most recent earnings announcement, as shown in equation 3.2 below:

$$Q_{it} = [(Q_{it} + Q_{it-1} + Q_{it-2} + Q_{it-3}) - (Q_{it-4} + Q_{it-5} + Q_{it-6} + Q_{it-7})] / P_{it-4} \dots\dots\dots (3.2)$$

The choice of P_{it-4} is to ensure that the stock price, used in normalising quarterly earnings change, is free from any sort of information contamination from the most recent earning announcement news. I use the above metric to measure the change in the representative investor's expectations of earnings growth. This represents a measure of the surprise that the investor faces each time a firm's quarterly earnings are announced.

The Consistency metric is the sequence of quarterly earnings changes and is constructed by using the most recent annualised quarterly earnings change deflated by prior year end stock

price. Consistency is the quarterly earnings change sequence lengths of 2, 3,, and 12 denoting either consistent rising, or declining in quarterly earnings changes lasting for 2 quarters, 3,, and 12 consecutive quarters respectively. Sequences of consecutive rises in quarterly earnings change are denoted as positive while the converse is true for sequences of consistent quarterly earnings falls.

The investor's response to the 'Consistency' proxy will depend on both the sign and intensity of the sequence of quarterly earnings change. Intensity here refers the length of the sequence. The consistency of the quarterly earnings change sequence for each of the companies is measured over a period of twelve calendar quarters. The consistency of a sequence of earnings changes forms a time series for each company over the sample period. For each of the companies, I compute the consistency of earnings change rises or falls, looking at each company's sequence over a period of twelve calendar quarters. The rationale for choosing twelve quarters is because it is known in the finance literature that momentum hardly lasts for more than three years; in fact, it is documented that long-term reversal of trends usually sets in after three years from when the initial trend started²².

3.4.3 The standardised unexpected earnings (SUE)

I construct the standardised unexpected earning (henceforth SUE) metric to measure the level of change in expected earnings that the representative investor faces at quarterly earnings announcements using consensus analysts' forecasts and actual quarterly earnings. Foster *et al* (1984) provide methods for constructing different kinds of SUE metrics along with their scaling formats. In the behavioural finance literature, the magnitude and sign of the SUE is used to explain the investors' (market) response to earnings news while they adjust to the difference between the announced earnings and expected earnings (Bernard and Thomas (1989, 1990), Brown *et al* (1987a, 1987b)). In other words, the information in SUE captures the intensity of the sentiment that investors display as they underreact to the most recent quarterly earnings news. In the past four decades, different measures have been used by researchers to calculate the standardised unexpected. In early research literature, SUE is constructed using the quarterly earnings first order auto-regressive data-generating model of the type shown in equation 3.3 below:

$$E[Q_{it}] = \delta_i + Q_{it-4} + \theta_i(Q_{it-1} - Q_{it-5}) + \theta \varepsilon_{it-4} + \varepsilon_{it} \dots\dots\dots (3.3)$$

where Q_{it} is the company i 's quarterly earnings per share in quarter t and δ_i is the drift term, while Q_{it-1} to Q_{it-5} represent the prior earnings-per-share value in periods $t - 1$ and $t - 5$. Bernard and Thomas (1989, 1990) document that although equation 3.3 is the true data-

²² See De Bondt and Thaler (1985), Jegadeesh and Titman (1993).

generating process, when forecasting earnings, investors omit the first order auto-regressive term $[\Phi(Q_{it-1}-Q_{it-5})]$ from their model and think that quarterly earnings are generated by $[E[Q_{it}] = \delta_i + Q_{it-4}]$ instead. By doing this, the investors introduce error into their forecasting models. Liu *et al* (2003) observe that equation 3.3 contains a seasonal random walk, with or without a drift, as seen in a special case where $\theta_i=0$ or $\delta_i=0$. Using this model, *SUE* is defined as the unexpected earnings deflated by the standard error of unexpected earnings. This measure of *SUE* calculates the earnings surprise based on the time series of the historical earnings realisations. Earlier works in the literature that adopt this model in calculating *SUE* include Latane and Jones (1977, 1979), Foster (1977), Foster *et al* (1984), Bartov (1992), and Brown (1993). These earlier models calculate *SUE* as:

$$SUE_{it} = \frac{UE_{it}}{\sigma UE_i} \dots\dots\dots (3.4)$$

where $UE_{it} = Q_{it} - E[Q_{it}]$, $E[Q_{it}]$ is the expected earnings from the univariate time series model, Q_{it} is the company *i* actual earnings in time *t*, and σUE_i is the standard error from the time series regression equation.

In chapter 5, I adopt similar metric (*SUE*) but measure it differently to reflect a more recent practice in literature. Furthermore, there is a general consensus in the literature that the earnings surprise metric constructed from the consensus analyst forecast explains stock returns better than that constructed with a univariate time series models of quarterly earnings-per-share²³. The method involves the use of the most recent consensus monthly analysts' forecast figure to proxy investors' expectation of future earnings. Based on the consensus monthly analysts' forecast and actual quarterly earnings per share in the most recent quarter, I calculate the standardised unexpected earnings, *SUE*, using the following model:

$$SUE_{it} = \frac{A_{it} - F_{it}}{P_{it-4}} \dots\dots\dots (3.5)$$

In equation 3.5 above, F_{it} represents the consensus monthly analysts' forecast for company *i* in the most recent month before the earnings announcement in time *t*. A_{it} is the company *i*'s actual quarterly earnings-per-share in time *t*, P_{it-4} is the prior year end stock price of company *i*'s share. Brown and Zmijewski (1987) is one of the early works to observe that analysts' forecasts of earnings are better at capturing earnings expectations than earnings forecasts made from time series models. The authors posit that the reason is because analysts are able to recognise and distinguish between permanent, transitory, and irrelevant earnings shocks, and therefore can adjust their forecasts more accurately. Furthermore,

²³ See Livnat and Mendenhall (2006).

analysts have more information about the political, regulatory and technology risks that companies face. In addition, other early work in the literature, such as Brown *et al* (1987a), Fried and Givoly (1982), Brown, Foster, and Noreen (1985), and Elton *et al* (1984), document that analysts' consensus forecasts of earnings capture the market's expectation of future earnings better than time series models. Brown *et al* (1987b) show that the reason for the superiority of the consensus analysts' forecast to the forecasts from the univariate time series models is not certain. However, the authors find that earnings surprises from the consensus analysts' forecast model explain the association between earnings expectation and stock returns better than time series models. In more recent literature, authors such as Livnat and Mendenhall (2006) document that consensus analyst forecast of earnings provides a better forecast than those of time series models in measuring *SUE*. Nguyen and Quang (2012) test the Livnat and Mendenhall (2006) model on the German stock market and their report suggests that consensus analysts' forecasts provide a better explanation of post-earnings announcement drift than the forecast derived from time series models. However, it is good to note that although time series forecasts might be less accurate, they might also be less biased, as analysts can be swayed by the 'bubble psychology'.

3.4.4 Computation of stock returns

Single period stock returns are calculated following the 'simple' returns measure from equation 3.6 below.

$$R_{it} = \frac{P_{it} + D_{it} - P_{it-1}}{P_{it-1}} \dots\dots\dots (3.6)$$

where R_{it} is the company i 's stock return at time t and P_{it} is the company i 's stock price at time t , P_{it-1} is the stock price in the immediate past period (the beginning-of-period stock price), and D_{it} is the dividend paid on the share during this period (for modelling purposes, I assume the dividend to be zero in all cases – this is a popular practice in literature). There is no consensus in the literature as to which method of calculating returns is preferred between the two main methods – the simple returns method and the compounding (logarithmic) returns method. Some researchers argue that the method the investor employs depends on the investment strategy that he follows. Others argue that for those investors that employ trading rules which involve rebalancing their stock portfolios periodically, the logarithmic returns method is the preferred method, while for those investors using a buy-and-hold strategy, the simple returns metric is the appropriate method. As documented by Barber and Lyon (1997), continuously compounded returns have negatively biased abnormal returns because of cross-sectional variation in the returns of common stocks. I do not consider the Dimson procedure of calculating stock returns appropriate for my sample. While the Dimson

procedure is appropriate for small and illiquid stocks, my data sample is composed of the S&P500 stock index constituent companies which represent the most capitalised and liquid stocks not just in the United States but in the whole world.

3.4.5 Benchmark expected returns (performance evaluation)

There is apparently no consensus in the literature as to which model is the best benchmark for measuring expected returns. Various forms of benchmarking that have been used in the literature include the control firm method; for example as used in Barber and Lyon (1997), Ang and Zhang (2004), and Kim, Klein, and Rosenfeld (2008). However, Ang and Zhang (2004) argue that the benefits of the control firm approach seem to be limited to small firms. Kim *et al* (2008) support the position of Ang and Zhang (2004) by observing that the control firm approach addresses the problem seen in standard models in that they do not capture the left tails of the distribution of firm size and trading prices. Barber and Lyon (1997) show that test statistics of abnormal returns calculated using benchmarks or reference portfolios such as the market index are miss-specified. The authors show that this miss-specification can be corrected by matching sample firms with control firms of similar sizes and book-to-market ratios. Moreover, Loughran and Ritter (2000) observe that this approach will be best for benchmarking in those studies where portfolio rebalancing is assumed. This is not the case with the portfolios in my thesis as they are buy-and-hold portfolios.

There are other types of models for measuring stocks' expected returns such as the Market model, the Market-adjusted model, the Capital Asset Pricing model (CAPM), and the factor models such as Fama-French's three-factor and Carhart's four-factor models. Ball (1978) and Fama (1991) document that there are large variations in the expected returns estimates across different benchmarks and that long-horizon results are sensitive to the model used in estimating expected returns. Fama and French (1993) also observe that the use of incorrect benchmark models in generating expected returns could result in systematic biases and miss-specification. However, Kothari and Warner in their 1997 paper posit that long-horizon tests for abnormal performance over a 36-month horizon produce similar results under the Fama-French three-factor model and other benchmark procedures. The authors examine a variety of abnormal returns from different models and document that the degree of miss-specification is not highly sensitive to the benchmark model employed, as suggested in earlier work.

More recent behavioural finance studies have adopted Fama-French's three-factor model and Carhart's (1997) four-factor models. Evidently, this is often because the robustness of the benchmark models which researchers previously used to calculate expected returns has been called into question. Fama-French (1992) observe that beta loses its explanatory

power in the presence of size and book-to-market ratio in a cross-section of stock returns and by implication the two-parameter capital asset pricing model (CAPM) is not the most robust benchmark model. In the literature, the more recent Carhart's four-factor model, which includes a momentum-related factor in addition to the Fama-French three-factor model, is argued to explain returns better than the Fama-French three-factor model. Ang and Zhang (2004) document that Carhart's four-factor model is inferior to a well-specified Fama and French three-factor model in a calendar-time portfolio because the four-factor model over-rejects the null hypothesis relative to the specified significance level. Furthermore, Ang and Zhang (2004) note that the Fama and French three-factor model has a relatively high power in detecting abnormal returns when compared with other benchmark models. Loughran and Ritter (2000) argue that if one uses positive (empirically based) models such as the three-factor model as a benchmark, it is not market efficiency that is being tested on this occasion. It is rather a test to ascertain whether a pattern exists which has already been captured by other well-known patterns. The authors argue that multifactor models such as the Fama-French three-factor model can be used as a benchmark only if the researcher believes that such models are equilibrium models, otherwise it is incorrect to use them as benchmarks. The size and book-to-market factors in the Fama-French three-factor model are regarded as priced systematic factors. The pattern of the anomaly (earnings momentum) I test is very distinct from the size and book-to-market effects in the Fama-French model. In studies of firm events involving managers' behavioural timing, such as stock splits, equity-financed acquisitions, seasoned equity offerings, and share repurchases, the Fama-French three-factor model tends to underestimate the abnormal returns (e.g. Loughran and Ritter (2000)). Of course my thesis examines the impact of earnings momentum on traded prices, so controlling for price momentum in benchmark portfolios could be interpreted as assuming what I seek to prove. Therefore, Carhart's four-factor model is not considered as an appropriate benchmark for my study.

3.4.5.1 The construction of the Fama-French type benchmark portfolios

I follow the Fama-French three-factor model (1992, 1993) in constructing the Fama-French type benchmark portfolios for my sample. The Fama-French three-factor estimation model is given by equation 3.7 below.

$$R_{pt} - R_{ft} = a_i + b_i(R_{mt} - R_{ft}) + s_iSMB_t + h_iHML_t + \varepsilon_{it} \quad \dots\dots\dots (3.7)$$

$$i = 1, \dots \dots N; t = 1, \dots \dots, T$$

R_{pt} is the simple return on the calendar-time portfolio p at time t , a_i is the regression intercept term, R_{mt} is the return on the value-weighted market index, R_{ft} is the monthly

return on a three-month Treasury bill. *SMB* is the size premium (small minus big) and represents the difference in returns of value-weighted small stocks portfolio and big stocks portfolio, while *HML* is the value premium (high minus low) and represents the difference in returns of value-weighted portfolios of stocks with high value (high book-to-market ratio) and portfolios of stocks of low value (low book-to-market ratio); b_{i,S_i} , and h_i represent the parameter estimates of the regression equation, while ε_{it} is the error term of the regression.

The Fama-French factor loadings (betas) are estimated using weights from rolling annual regressions for each of the six stock portfolios over five years of monthly data. My procedure for creating the six portfolios follows the Fama-French (1993) approach. First, I sort my firms into two portfolios by using their market equity (ME) to divide them into two equal big and small portfolios. Subsequently, each of the small and big ME portfolios are further sorted into three portfolios using their book-to-market ratio (the ratio of book equity to market equity). The market equity is based on a stock's market equity at the end of June in each year of my sample period. The BE/ME breakpoints are at the 70th and 30th percentiles which represent the growth, neutral or medium, and low or value portfolios respectively. This exercise creates six stock portfolios: the Big-High (BL), Big-Medium (BM), Big-Low (BL), Small-High (SH), Small-Medium (SM), and Small-Low (SL) portfolios at the point of intersection of the size (ME) and BE/ME breakpoints.

I form 96 different Fama-French type calendar-time portfolios across 16 different portfolio formation periods (years) to estimate factor loadings for my sample period of between 1991 and 2006. For the estimation of the Fama-French betas, I use sample data beginning from January 1986 in order to obtain enough data (60 months) for the estimation of factor loadings for the year 1991, the first year of my sample period. I use the estimated factor loadings (betas) and the corresponding Fama-French benchmark factor returns to calculate the expected returns for each of my six portfolios above (in each year of my sample period). To measure the expected return on each of the stocks, I match each stock to the relevant six Fama-French benchmark portfolios. I use the market capitalisation of each stock and its book-to-market ratio as criteria for matching the stocks to their appropriate portfolio returns. Each of the stocks must have 60 months of contiguous pre-estimation returns, or at least have a minimum of historical contiguous returns for 24 months.

I employ the value-weighted approach in the construction of the portfolios. Some previous research argues that the returns of equal-weighted portfolios outperform both the value-weighted and price-weighted portfolios (see Plyakha, Uppal, and Vilkov (2012)). However,

the majority of researchers also observe that this is more likely to happen with small stocks rather than large stocks like the S&P500 constituents stocks I study here²⁴.

In chapter 5, the estimation of beta or the Fama-French factors loading are repeated following the same procedure as above but using daily data in place of monthly data.

3.4.5.2 Measuring abnormal returns

In the literature, many researchers recommend the buy-and–hold abnormal returns (BHAR) strategy over the cumulative abnormal returns (CAR) strategy. Researchers such as Roll (1983), Blume and Stambaugh (1983), and Conrad and Kaul (1993) argue that the additive nature of the cumulative abnormal returns strategy means that it is usually positively biased because of the effect of the bid-ask spread. Barber and Lyon (1997) document that the apparent contradictory results findings between cumulative abnormal returns and buy-and–hold abnormal returns may be down to the impact of a number of biases such as new listing, rebalancing, and skewness on cumulative abnormal returns and buy-and–hold abnormal returns (see also Dissanaike (1994)). However, Barber and Lyon (1997) favour buy-and–hold abnormal returns over cumulative abnormal returns and posit that buy-and–hold abnormal returns perform better in the short to medium-term horizon than the long-run horizon. Although I employ buy-and–hold abnormal returns in this investigation, my method of computing the expected returns differs slightly from Barber and Lyon’s (1997) procedure. While they employ the use of appropriate asset/portfolio expected returns, I use the same sample firms (S&P500 constituent firms) to construct the expected returns using the Fama and French three-factor model, hence the problem of new listing bias does not arise.

Fama (1998) argues that the problems associated with drawing statistical inferences from long-term returns increase as the return horizon lengthens. He, however, posits that inferences of long-term returns should be made based on averages or cumulative abnormal returns (CAR), rather than buy-and–hold abnormal returns (BHAR). In similar studies, Barber and Lyon (1997) and Kothari and Warner (1997) argue that the problem of drawing statistical inferences with BHARs usually occurs with a long horizon of greater than three years. In this study, I employ time-horizons of up to three months, which means that I am unlikely to face the problem outlined by the authors above.

In chapter 4, I use the buy-and–hold abnormal returns (BHAR) strategy to measure the abnormal returns between the expected return and the raw return in the month following a quarterly earnings announcement. In chapter 5, I use the BHAR strategy to measure abnormal returns around a three-day event window surrounding the quarterly earnings

²⁴ See Plyakha, Uppal, and Vilkov (2012).

announcement date. Some previous studies argue that the buy-and-hold strategy reflects how investors calculate abnormal returns in practice better than the alternative strategy (cumulative abnormal returns – CAR) (see Barber and Lyon (1997)). The cumulative abnormal returns strategy requires that investors continuously rebalance their stock portfolios by selling loser stocks and buying winner stocks, and this comes with attendant large trading costs. For the first empirical chapter, I measure my buy-and-hold abnormal returns over a medium-term period of between one and three calendar months after the earnings announcement. In the second empirical chapter, I calculate the buy-and-hold abnormal returns over a window of three days beginning a day prior to the earnings announcement date to measure the post-earnings announcement drift associated with the earnings announcement.

To calculate the abnormal returns, I match my sample stocks with each of the six size/value portfolios I created in section 3.4.5.1 above. I use the individual stocks' market equity and book-to-market ratio to sort them into six different groups, directly matching them to each of the six portfolios.

I follow Barber and Lyon's (1997) and Ang and Zhang's (2004) approach in calculating my abnormal returns and subsequently the buy-and-hold abnormal returns. I define R_{it} as the simple returns for firm i at time t , and calculate the firm i abnormal returns at time t as ABR_{it} , and $E(R_{it})$ as the expected return on my sample firm i at time t .

$$ABR_{it} = R_{it} - E(R_{it}) \dots\dots\dots (3.8)$$

I also calculate the cumulative abnormal returns (CAR), for a robustness check with my main strategy, the buy-and-hold abnormal returns.

$$CAR_{it} = \sum_{t=1}^T AR_{it} \dots\dots\dots (3.9)$$

where CAR_{it} is the company i abnormal returns cumulated from time t to time T .

3.4.5.3 Buy-and-hold abnormal returns (BHAR)

I calculate the buy-and-hold abnormal returns on my sample stocks over three calendar months beginning with the month of the most recent earnings announcement and the two months following the earnings announcement month. The buy-and-hold abnormal returns are computed as shown in equation 3.10 below:

$$BHAR_{it}(t_1, T) = \prod_{t=1}^T (1 + R_{it}) - \prod_{t=1}^T (1 + E(R_{it})) \dots\dots\dots (3.10)$$

$BHAR_{it}(t_1, T)$ is company i 's buy-and-hold abnormal return from t_1 to T , R_{it} is the actual return for company i at time t , and $E(R_{it})$ is the expected return for company i at time t . My cumulative abnormal returns (CAR) are highly correlated to the BHAR, suggestive of the fact that similar results are likely if CAR, rather than BHAR, is used in the regression and test analysis. So the return metric chosen is expected to alter the quantitative but not the qualitative nature of my reported results in chapters 4 and 5.

3.4.5.4 Buy-and-hold abnormal returns (BHAR) (short window)

I repeat the procedure in section 3.4.5.3 above to calculate the buy-and-hold abnormal returns for the short window of three days in chapter 5. This is to capture the post-earnings announcement drift over the days around the earnings announcement date. I use a day prior to the earnings announcement date as the starting point and cumulate/multiply returns up to a day after the announcement date. This approach follows Bernard and Thomas (1990), who document that a delayed market reaction to earnings news is captured within the three-day window around the earnings announcement date. The authors reported that although the three-day window represents only 5% of the total trading days in a quarter, their results show that the announcement period reactions in the three-day window represent a disproportionate share of the post-earnings announcement drift. Similar approaches are reported by Bernard and Thomas (1989), Freeman and Tse (1989), and Jegadeesh and Titman (1993).

3.4.6 Information uncertainty

Information uncertainty, also known as value ambiguity, is defined as the ambiguity surrounding the implications of new information on a firm's fundamental value. Zhang (2006a) posits that information uncertainty is brought about by poor information and the volatility of a firm's underlying fundamentals. In their paper, Jiang, Lee, and Zhang (2005) document that firms with high information uncertainty are very likely to show strong price momentum and post-earnings announcement drift when conditioned on the nature of the news. This follows directly from the fact that high information uncertainty is likely to lead to greater expected returns after good news and smaller, or even negative, expected returns after bad news when compared to firms with lower information uncertainty. This is the interaction effect between information uncertainty and the nature of news (measured by the sign and magnitude of earnings surprise). The authors also show that high information uncertainty firms earn lower future stock returns than low information uncertainty firms in a univariate regression analysis. This is the mean effect of information uncertainty on stock returns. Zhang (2006a) argues that if investors underreact to new information about firms

such as earnings announcements, the underreaction will be stronger in the presence of high information uncertainty, which an earnings announcement might be expected to partially resolve. In a similar study, Jiang *et al* (2005) document that information uncertainty proxies have high interaction effect with earnings momentum proxies, i.e. SUE, and consensus analysts' revision strategies show a much stronger effect with high information uncertainty firms than with low information uncertainty firms.

In chapter 5, I introduce information uncertainty variables into the original model, for two reasons: first, to examine how much of the abnormal performance can be attributed to the level of information uncertainty surrounding the firm's underlying fundamentals; second, to examine by how much the abnormal performance attributed to the influence of the gambler's fallacy (as proxied by the streaks of earnings surprises) still remains in the presence of the uncertainty of a firm's value. Put another way, I seek to ascertain whether the information uncertainty about firms' fundamentals subsumes (or magnifies) the effect of streaks of earnings surprises on prices in very short windows. Are streaks in companies' quarterly earnings surprises subject to high informational uncertainty more or less likely to help resolve that uncertainty and so intensify the streak's impact on prices?

3.4.6.1 Information uncertainty proxies

I employ a number of fundamental measures to capture the information uncertainty surrounding the firm's stock value at the arrival of earnings news. The proxies include the firm's Market Capitalisation (MCAP), firm age (AGE), analyst coverage of a firm (ACOV), analysts' forecast dispersion (AFORD), cash-flow volatility (CVOL), and standard deviation of the stock's weekly excess market returns (SVOL). I follow Zhang's (2006a) procedures in measuring the selected information uncertainty proxies. I use the information uncertainty proxies for two major reasons: first, because they capture the fundamental volatility associated with the stocks, and second, because they capture the noise. Noise in itself magnifies the level of ambiguity around a firm's fundamental value.

I use information uncertainty proxies in order to examine:

- Their mean effects on post-earnings announcement drift and
- Their interaction effects on post-earnings announcement drift with streaks of quarterly earnings surprises.

3.4.6.1.1 Market capitalisation (MCAP)

This is the market value of the company's stock (in millions of dollars) at the end of the last month (December) of the prior year. It is my opinion that this measure of information uncertainty clearly distinguishes companies from one another, since smaller companies will have less information available to investors than larger companies. This is a slightly different interpretation to the 'size' effect documented by Fama and French (1992), who stress the riskiness of small stocks. Smaller firms (some of which are often young firms as well) may have a less-established business history, lower or narrow customer base, and shorter dividend payment or omission history. As a result, there may not be much information about them in the public domain. This comes with a challenge, in that investors who are keen on obtaining certain key and important information about these firms will have to incur search and information acquisition costs. Zhang (2006a, 2006b) argues that although firm size may be a good proxy for information uncertainty, it is likely to be noisy. It is likely to contain other information about various firm events and issues, hence any inference coming directly from it is likely to be contaminated. Nevertheless, the size of a firm carries a great deal of information about the firm, and so it is intuitive that I should include it as a proxy for information ambiguity. Hong, Lim, and Stein (2000) posit that with information acquisition costs fixed across firms of different sizes, paying for information for small firms would not be attractive to investors. The authors argue that this will lead to less information on smaller firms being available in the market, which will increase information uncertainty around those firms. In this study, I focus on the substantial size variation within the largest US companies listed on the US S&P500 stock index.

3.4.6.1.2 Firm age (AGE)

I define firm age here as the number of years starting from the date the company was added to the S&P500 list of constituent companies to the sample date. Older firms in the S&P500 index will have a significantly longer history of available public information than younger firms in the index. Most often, the older firms are the more established in terms of business history and are more likely to be run by highly respected management teams than younger firms (Zhang 2006a). I therefore use the firm's age as one of the proxies to capture the information uncertainty brought about by the length of time through which a firm has 'survived' in the S&P500 index. It is expected that only profit-making and well-managed firms will stay in the index for a long period of time without being deleted. I hypothesise that younger firms have high information uncertainty as compared to older firms. Pastor and Veronesi (2003) document that individual firm's uncertainty decreases during their lifetime and that the stocks of young firms are more volatile than those of old firms. In addition, Barry

and Brown (1985) observe that firms for which there is relatively little information (young firms) show higher parameter uncertainty. Put in a different way, there is higher uncertainty in model parameters measured for firms with limited information.

3.4.6.1.3 Analyst coverage (ACOV)

Analyst coverage is the total number of analysts following a company. It is the number of analysts providing fiscal year earnings forecasts for the company in each month. Investors and other market participants sometimes depend on analysts' opinions and recommendations about firms' future performance for investment decisions. Analysts do not follow and report on all firms equally. The number of analysts following firms and the amount of information and analysis they provide on these firms differ widely across firms. It is widely known in the literature that the higher the analyst coverage for a firm, the more information on the firm is available to market participants. This is likely to lead to less information uncertainty about those firms that have high analyst coverage. Lang and Lundholm (1996) report a relation between firms with more information disclosures and a large number of analysts following them, and also that those firms have more accurate analyst earnings forecasts. Thus, there is less divergence in individual analyst forecasts of a firm's earnings and less volatility in analysts' forecast revisions for such firms. However, it is important to remember that analysts are affected by 'herd' behaviour, in that they agree 'too much' with the most popular forecasts, as observed by Gleason and Lee (2003). This shows that the informativeness of analysts' reports and information disclosures are complementary to each other, even though they should be substitutes. Bhushan (1989) links the cross-sectional variation in information content of firms' earnings announcements with differences in the number of analysts following those firms. Gleason and Lee (2003) document that in post-revision drift, the stock price adjusts faster for firms with large analyst coverage and their price shows less drift. Hong, Lim and Stein (2000) support the idea that the effect of large analyst coverage is more pronounced for stocks that are past losers than for past winners. This assertion suggests that investors are keener to quickly assimilate analysts' information on past loser stocks than that on winner stocks. However, it is important to note at this point that these authors have deleted the smallest companies from their sample data prior to carrying out their analysis.

3.4.6.1.4 Analysts' forecast dispersion (AFORD)

I use the dispersion in analysts' forecasts of quarterly earnings as one of my information uncertainty proxies. This is defined as the standard deviation of consensus analyst forecasts about a firm's quarterly earnings in the most recent month, deflated with the prior year end stock price. If a firm has large (small) analyst forecast dispersion, this is an indication of high

(low) uncertainty about the firm's future earnings. A number of researchers have used analyst forecast dispersion as a proxy to measure the level of consensus across analyst forecasts or market participants or uncertainty about a firm's future earnings. These include Zhang (2006a, 2006b), Barron *et al* (1998), Barron and Stuerke (1998), Diether, Malloy, and Scherbina (2002), Imhoff and Lobo (1992), and Lang and Lundholm (1996). Barron and Stuerke (1998) find a positive relation between analyst forecast dispersion and stock price reaction around subsequent earnings announcements. Imhoff and Lobo (1992) document that there is a systematic relation between *ex ante* uncertainty (proxied by the variance of analyst forecast dispersion) and the information content of earnings announcements. These pieces of evidence show that dispersion in analyst forecasts is a measure of ambiguity about a firm's fundamental value around the earnings announcement date.

3.4.6.1.5 Cash-flow volatility (CVOL)

Cash-flow volatility is measured as the standard deviation of monthly cash-flow from operating activities over a period of three years. Following Zhang's (2006a) approach, I treat stocks that have less than three years data as missing. This is the cash from the firm's operating activities representing cash receipts and disbursements resulting from the operations of the firm. The cash-flow which is calculated indirectly from the firms' financial statements is likely to capture volatility surrounding the fundamental value of the firm. Huang (2009), using standard deviations of cashflow-to-sales and cashflow-to-book equity to proxy for cash-flow volatility, finds a strong relation between cash-flow volatility and future stock returns. According to him, the least volatile decile portfolio outperforms the most volatile decile portfolio by 13% per annum, using the Fama and French three-factor model as a benchmark.

3.4.6.1.6 Standard deviation of stock weekly excess market returns (SVOL)

This is a measure of a stock's return volatility. It is measured as the standard deviation of the stock's weekly excess market returns over the S&P500 index. Again, following Zhang (2006a), I estimate the standard deviation of a stock's weekly excess market returns over one year period. This is a measure of 'total risk', like the Sharpe ratio, and not just the idiosyncratic risk which might not expect to be priced in an efficient market. Ang *et al* (2009) consider volatility in stocks from around the world and argue that those stocks with recent high volatilities have low future average returns.

3.5 Robustness check

3.5.1 Monthly analyst forecast revision

To check the robustness of my measures of earnings surprises in the first and second empirical chapters, I introduce the monthly analyst forecast revision which captures the change in the investors' expectation of earnings. In the same manner as other earnings surprise metrics, the analyst forecast revision here is used as a measure of earnings surprise (or at least innovations in investors' expectations about future earnings). It is measured based on the changes in the median in the analyst earnings forecast over the most recent six months (reported monthly). Liu, Strong and Xu (2003) document that analyst forecast revision has the advantage of providing a timely measure of the earnings surprise. Chan *et al* (1996) document that since analysts do not necessarily revise their forecast every month, some months will have zero value for the analyst revision. To overcome this problem, they use a six-month moving average of past revisions in analysts' earnings forecasts rather than using the raw monthly figures. I follow Chan *et al*'s (1996) approach to measure the analyst forecast revision.

$$REV6_{it} = \sum_{j=0}^6 \frac{f_{it-j} - f_{it-j-1}}{P_{it-j-1}} \dots\dots\dots (3.11)$$

$REV6_{it}$ is the six-month moving average of past months' analysts' forecast revisions, f_{it} is the consensus mean I/B/E/S estimate in month t of firm i 's earnings for the current fiscal year. The analysts' monthly revisions of earnings are deflated by the prior month's stock price P_{it-j-1} .

3.6 Estimation and testing techniques

Panel data fixed effects and pooled ordinary least squares multivariate regression models are employed to estimate the effects of sequences of quarterly earnings changes and streaks of earnings surprises on the abnormal returns of my S&P500 sample stocks. The parameter estimates are tested at a medium-term window of three months and a short-term window of three days. The panel data estimation method is the main estimation method employed, while the pooled ordinary least squares estimation method is only employed for robustness checks.

3.6.1 Regression analysis

Panel data regression is the main regression model employed in this research work. I employ the fixed effects panel data model estimation method in both empirical chapters. Based on the fact that my model is a representative agent model, fixed effect panel data estimation is the estimation method of choice because it is able to eliminate fixed effects (individual firm unobserved effects). Notwithstanding the fact that my data sample is composed of the S&P500 constituent companies, these are companies from different industry sectors of the US economy. Using the fixed effects estimation method ensures that the idiosyncratic characteristics (heterogeneity effect) of firms that might affect the response variable are controlled. Klevmarken (1989) and Hsiao (2003) enumerate the benefits of panel data estimation:

- Controls for individual heterogeneity.
- Panel data give more informative estimates, more variability, less collinearity among the variables, more degrees of freedom and more efficiency.
- Panel data are better able to capture the dynamics of adjustment.
- Panel data are better able to identify and measure effects that are simply not detectable in pure cross-section or pure time series data.
- Panel data models allow us to construct and test more complicated behavioural models than pure cross-section or pure time series data.
- Micro panel data gathered on individuals, firms, and households may be more accurately measured than similar variables measured at macro level. Biases resulting from aggregation over firms or individuals may be reduced or eliminated (Blundell (1988); Klevmarken (1989)).
- Macro panel data on the other hand have a longer time series, and unlike the problem of nonstandard distributions typical of unit root tests in time-series analysis, Baltagi (2005) shows that panel unit root tests have standard asymptotic distributions.

In general, I estimate a one-way fixed effects panel data regression model of the type shown in equation 3.12 below:

$$y_{it} = \beta_0 + x_{it}\beta + a_i + u_{it} \dots\dots\dots (3.12)$$

where y_{it} is the dependent variable BHAR observed for company i at time t , x_{it} is a vector of independent variables for individual company i across different time periods t , a_i is the unobserved effect (e.g. management philosophy, management quality etc. for each individual company) for company i which is fixed over time, and u_{it} is the error term. The full model specifications are shown in the respective empirical chapters. To eliminate company-specific unobserved effects from the estimation, for each company i equation 3.12 is averaged over time to get:

$$\bar{y}_i = \beta \bar{x}_i + a_i + \bar{u}_i \dots\dots\dots (3.13)$$

where $\bar{y}_i = T^{-1} \sum_{t=1}^T y_{it}$, $\bar{x}_i = T^{-1} \sum_{t=1}^T x_{it}$, $\bar{u}_i = T^{-1} \sum_{t=1}^T u_{it}$

Subtracting equation 3.13 from equation 3.12 for each t gives:

$$y_{it} - \bar{y}_i = \beta(x_{it} - \bar{x}_i) + u_{it} - \bar{u}_i \quad t = 1, 2, \dots, T$$

or

$$\dot{y}_{it} = \beta \dot{x}_{it} + \dot{u}_{it} \dots\dots\dots (3.14)$$

Where \dot{y}_{it} , \dot{x}_{it} , and \dot{u}_{it} are time-demeaned data on y , x , and u respectively. Equation 3.14 is the fixed effect estimator, or the within estimator, and the most important point is that the unobserved component, a_i , has disappeared from the model.

3.6.2 Pooled ordinary least squares regression analysis

I also employ pooled ordinary least squares estimation as a means of checking for the robustness of my panel data estimation in section 3.6.1 above. Again, the model estimated here is of a general form, as in equation 3.13 below:

$$y_{it} = \beta x_{it} + \epsilon_{it} \dots\dots\dots (3.15)$$

The key assumption here is that the error term ϵ_{it} is independently identically distributed over time t and individual firms i , and unobserved effects are assumed not to be correlated with the explanatory variables. Since the error term is *i.i.d.*, the double index (i, t) is seen as not necessary, on the assumption that no information is lost by creating a new index, say j , and treat the data as though they were generated by equation 3.16 below:

$$y_j = \beta x_j + \epsilon_j \dots\dots\dots (3.16)$$

In equation 3.16, the error term is assumed to be *i.i.d.* over i and t , therefore it should be *i.i.d.* over j . Since this is the case, this brings us back to the classical linear regression setting

with all the assumptions of an OLS estimator. The observations of x_{it} are stacked in a matrix X and the observations of y_{it} are stacked in a column vector Y . Equation 3.16 is thus estimated.

3.6.3 Testing the statistical significance of the abnormal returns

I employ a t-test to make inferences about the statistical significance of the mean of estimated BHAR. In the second part of chapter 5, the information uncertainty proxies and the streaks of earnings surprises are used to sort the three-day buy-and-hold Fama-French three-factor adjusted returns. First, each information uncertainty variable and the mean of the past 11-month returns are employed to single-sort $BHAR_{-1,1}$ to determine the variables mean effects on BHAR. Second, each information uncertainty variable is divided into two portfolios of high and low information uncertainty by their median value. This procedure is carried out separately for both the positive and negative streaks in quarterly earnings surprises. Then $BHAR_{-1,1}$ is sorted by positive streaks of quarterly earnings surprises and subsequently sorted by each information uncertainty variable into high and low information uncertainty portfolios. This procedure is again repeated with stocks with negative streaks in quarterly earnings surprises. This is the interaction effect between each information uncertainty variable and the streaks of earnings surprise on $BHAR_{-1,1}$. I employ t -statistics, estimated using the cross-sectional variation of the three-day buy-and-hold Fama-French three-factor adjusted returns, in order to test for the statistical significance of the $BHAR_{-1,1}$. Specifically, for the information uncertainty variable's mean effect to test the null hypothesis that the mean of $BHAR_{-1,1}$ is equal to zero for the portfolio of n stocks, I compute the t -statistics as follows:

$$t_{BHAR} = \frac{MBHAR}{\sigma_{BHAR}/\sqrt{n}} \dots\dots\dots (3.17)$$

where $MBHAR$ is the portfolio return's arithmetic mean, σ_{BHAR} is the cross-sectional sample standard deviation of the three-day buy-and-hold Fama-French three-factor adjusted returns, t_{BHAR} is the computed t -statistics, and n is the number of stocks in the portfolio.

To test the interaction effect between the information uncertainty variable and streaks of quarterly earnings surprises on $BHAR_{-1,1}$, I test the significance of the difference portfolio (HML) between portfolios of high information uncertainty (HIU) and portfolios of low information uncertainty (LIU) using a two-sample t-test, as shown in equation 3.18 below:

$$t_{BHAR_{HML}} = \frac{MBHAR_{HIU} - MBHAR_{LIU}}{\sqrt{\frac{2S^2}{N}}} \dots\dots\dots (3.18)$$

The sample variance is computed as in equation 3.19 below:

$$S^2 = \frac{S_{LIU}^2 + S_{HIU}^2}{2} = \frac{\sum_{n=1}^N (BHAR_{LIU} - MBHAR_{LIU})^2 + \sum_{n=1}^N (BHAR_{HIU} - MBHAR_{HIU})^2}{2(N-1)} \dots\dots\dots (3.19)$$

Chapter 4

Earnings momentum models, sequences of quarterly earnings change, and stock market response

4.1 Introduction

In chapter 3, I outline and describe my sample data and the various methods employed in the empirical analysis of the data. In this first empirical chapter, I test the response of stock prices to sequences (streaks) of changes in quarterly earnings-per-share (EPS) for my sample frame. To do this, I apply some of the propositions of two of the simplest representative agent earnings momentum models, Rabin (2002b) and Barberis, Shleifer and Vishny (1998) to predict stock market response to earnings announcement. The two models are parsimonious and tractable. A good theory should be able to explain much by little in terms of its assumptions and complexity (Friedman, 1953). A simple theory which requires many restrictive assumptions but predicts well can effectively encompass a more realistic but less predictively accurate alternative. In this chapter, through the various analyses of my sample data, I inquire whether there is more to earnings momentum than these very simple models explain. I also examine some of the contrasting predictions of the two models to ascertain which fits the historical data better. There is now substantial evidence in the literature showing that the stock market fails to process earnings information adequately. Such stock market behaviour is deemed anomalous in the face of new information about companies' fundamentals coming into the market. To be deemed 'anomalous', the stock market's response to earnings must deviate from that of a rational (reasonable) investor. A rational investor in the traditional finance literature is one who forms his expectation of earnings outcomes in accordance with Bayes' rule. Hence any deviation by investors from a Bayesian inference about future earnings outcomes casts doubt on models that invoke rational inference about corporate fundamentals for equity valuation.

This chapter also examines the completeness of the information content of the innovation in quarterly earnings and its use for equity valuation. Prior evidence in the literature shows that the difference between the most recent quarterly earnings and that of the same quarter last year constitutes the innovation in the most recent quarterly earnings (Ball and Brown (1968), Bernard and Thomas (1989, 1990)). This is based on the assumption that investors look at last year's quarterly earnings as the best predictor of earnings in the same quarter of the current year. So, the quarterly EPS last year serves as the expected EPS for the same quarter this year. In standard finance, innovation in quarterly earnings always has a zero expectation, since earnings are supposed to follow a random process. However, evidence shows that the majority of the time, innovation in earnings is a non-zero figure, and this is the

'earnings surprise' to investors. The term 'earnings surprise' in standard market-based finance models represents a movement in earnings outcomes that does not accord with Bayesian projections. Most commonly, earnings surprise is measured as the difference between the actual quarterly EPS outcomes and investors' expectations of them. Many studies show that the stock market responds in the direction of the most recent earnings surprise; if the surprise is above investors' expectations, there is a positive short-run continuation in stock price (PEAD) in the direction of the sign of the earnings surprise and vice versa. There are a number of academic papers that have sought to explain why market returns deviate from the projections of rational expectation model. Some attribute this anomalous behaviour of the stock market to a number of cognitive biases that influence investors' decision-making process. Leading the large number of psychological biases which have received a lot of attention in research are underreaction and overreaction anomalies. This chapter particularly studies the matching short-run anomaly of stock market underreaction based on investors' failure to fully take into account recent information about earnings into their expectations of stock prices²⁵. Investors' underreaction to earnings news show that a company's average stock returns in periods following good news (when earnings surprise is positive) are higher than the average returns in periods following bad news (when earnings surprises are negative). I study this behaviour by examining the response of three-monthly buy-and-hold abnormal returns to sequences of quarterly earnings announcements for the S&P500 constituent companies in the years 1991 to 2006.

The first issue to be examined in this chapter is the distribution of sequences of quarterly earnings changes across the sample of S&P500 companies. This is important because the two models mentioned earlier have contrasting predictions as to what the distribution of this sequence of earnings should be. In examining this, it will be interesting to see which of the two models fits well with the distribution seen in the observed stock market data, at least for my S&P500 sample data frame. The central argument in this thesis presents a mechanism for stock market responses to specified sequences of earnings surprises. I begin by examining what this response is when there is positive trending in earnings, as against when reversal in earnings occurs. Although the investors are 'surprised' when the earnings deviate from the expected, one would like to examine how 'surprised' they are with companies that have recently reported streaks of earnings surprises of a particular sign. In other words, in examining the response of the market to sequences of earnings surprises, is there a point at which investors learn? Or are investors like 'frogs in the pan' and are less responsive to a series of small shocks than one large jolt?²⁶ This relates to a more fundamental question

²⁵ See Chan *et al* (1996).

²⁶ See Da *et al* (2014) for full details of the frog-in-the-pan hypothesis.

about how the market aggregates information (see Hayek (1937)). One of the predictions of Barberis *et al*'s (1998) model is that the representative investor uses a quasi-Bayesian model (an incorrect model, incorporating a sluggish response to news) in forecasting earning outcomes, and never realises that the model he is using is incorrect. On the other hand, Rabin (2002b) posits that if individuals are uncertain about the rate generating a particular process (e.g. an earnings-generating process), they overinfer from short sequences of its signals in a manner that suggests that the rate is more extreme than it actually is.

4.2 Related literature

Chan *et al* (1996, 1999) find that changes in earnings expectations have an incremental ability to predict monthly returns, over and above that of previous returns themselves. In drawing this conclusion, Chan *et al* (1996, 1999) accord with earlier evidence that investors struggle to understand both how earnings are constructed and what they imply for price. The same problem is identified by Kaplan and Roll (1972), who observe that although investors do require and work with accounting information, as contained in accounting statements, the sheer complexity and diversity of business transactions in accounting statements mean that investors' understanding of them is limited. If this was true in 1972, we might think it to be far truer today, with the huge increase in the quantity and variety of accounting disclosures over published accounts of 200 pages or even more for large companies like my S&P500 sample companies.

The many empirical studies of earnings momentum cluster into three broad categories based on the earnings surprise proxy used:

- Bernard and Thomas (1989, 1990) conducted influential studies on post-earnings announcement drift. Post-earnings announcement drift is the phenomenon which sees companies with good news about earnings outperforming those with bad news for some months following the earnings announcement. Good (bad) earnings news here is described as a situation where the actual earnings outcome is higher (lower) than the expected earnings. Subsequently a number of researchers have related the intensity of this phenomenon to transaction costs, arbitrage and liquidity risks (Bhushan (1994), Mendenhall (2004), Sadka and Sadka (2009)).
- Chan *et al* (1996, 1999) confirm the ability of revisions in the consensus analysts' forecasts of earnings to predict the degree of earnings momentum in the US. This evidence has been available at least since Givoly and Lakonishok (1979)

confirmed the predictive power of analysts' consensus forecast revisions for stock market returns.

- Easton *et al* (1992) document the degree to which earnings changes and price changes correlate in the long run. This result simply extends and makes more powerful the original result of Ball and Brown (1968) which shows that earnings changes and subsequent price changes correlate. This suggests that markets struggle to process earnings information and fail to incorporate such information instantaneously into price as the efficient market theory suggests.

Since Chan *et al*'s (1996, 1999) early results, a number of studies have confirmed the presence of earnings momentum both in the US and elsewhere in the world and the need to explain why it persists. Griffin *et al* (2005), and Leippold and Lohre (2012) both document the presence of momentum in the international stock markets. Leippold and Lohre (2012) find that both price and earnings momentum are present in international equity markets and yet cannot establish any link between momentum and broader macroeconomic risks. They conclude that the only plausible explanation for the presence of momentum is that investors underreact to fundamental news about firms. Their work seems to confirm the work of Griffin *et al* (2005) who find momentum in global equity portfolios. Griffin *et al* (2005) find that price and earnings momentum strategies are profitable on a global basis. Other papers have previously reported the profitability of momentum strategies in Asian, European, and many emerging markets²⁷.

While each of these studies confirms the widespread presence of both earnings and price momentum, they differ on whether these are different manifestations of the same phenomenon or simply separate manifestations of asset mispricing. Could both earnings and price momentum occur as a result of the inability of the market to correctly interpret information about future cash-flows, or are they two independent phenomena? Chan *et al* (1996) find price momentum to be clustered around earnings announcements, suggesting price momentum is partly a response to earnings news. Chordia and Shivakumar (2006) find that in the US at least, price momentum is largely explained and subsumed by the systematic component of earnings momentum. Leippold and Lohre (2012) largely confirm this position for a sample of European markets.

Using consensus analysts' forecasts to study earnings momentum, Hilary and Hsu (2013) report results on the relation between the persuasiveness of an analyst's forecasts and the consistency of their forecast errors. Specifically, they report that consistent forecast errors

²⁷ See Rouwenhorst (1998, 1999), and Chui, Titman, and Wei (2000).

dominate forecast accuracy as a determinant of the informativeness of an analyst's forecast revisions. Furthermore, the authors report that to a greater extent, the consistency of analysts' forecast errors affect price more than the size and magnitude of single forecast error.

The papers reviewed above suggest that an understanding of earnings momentum will go a long way towards explaining the puzzling persistence of the momentum anomaly. Although a large body of empirical research on earnings momentum currently exists, we still lack compelling theoretical models to confirm whether earnings momentum and price momentum are the same phenomenon or two phenomena linked by a common causal process, and if so, what that process is. In this chapter I examine and present evidence from two such theoretical models from many alternatives on offer (of which Hong and Stein (1999) is one of the leading examples) to fulfil this role. This may help in providing complementary evidence to facilitate future theory-driven empirical investigation on earnings momentum.

4.3 Behavioural models of earnings momentum and hypothesis development

The representative agent framework envisages a prototypical 'everyman' investor facing different states of the world on different dates, say, in periods of boom and recession, good and bad, or momentum and reversion regimes. The investor conditions his response to earnings announcements according to the state of the world he currently believes to hold. In order to understand investors' responses to sequences of quarterly earnings changes within the US S&P500 data frame, I examine the predictive power of two such representative agent models by Barberis, Shleifer, and Vishny (1998) and Rabin (2002b). At the end of the empirical tests, I draw inferences from the results to find out which of these two models is supported by the evidence drawn from the real-world data.

4.3.1 Rabin's (2002b) inference by believers in the law of small numbers model

Rabin (2002b) considers the responses to information of an investor who is a standard Bayesian apart from believing that the urn, or population, from which he draws the observed sample outcomes (of, say, earnings), is sampled without replacement. This induces a form of the 'gambler's fallacy' that it is time for one's 'luck to turn' after observing a streak of successive (usually bad) outcomes. Rabin (2002b) terms such a deviant projection of outcomes a belief in the 'law of small numbers'. This is of, course, simply an imitation of the true rule of inference called the law of large numbers. Rabin (2002b) uses the term 'Freddy' to illustrate those individuals who believe in the law of small numbers. I adopt this terminology from Rabin (2002b) in referring to a believer in the law of small numbers as 'Freddy', who uses a sort of everyman quasi-Bayesian inference. In the following two

sections, the focus is on how a Bayesian and a Freddy differ in their projection of earnings outcomes given the recently observed sequence of quarterly earnings changes.

4.3.1.1 A Bayesian inference about earnings outcomes in the Rabin model

Consider a Bayesian investor faced with a recent sequence of quarterly earnings changes, for example, two consecutive increases in quarterly EPS or an increase followed by a fall. What weight does such an investor place on a further increase in quarterly earnings outcomes (Pr_{rise})? The answer is, of course, given by the Bayesian posterior inferred from multiplying the likelihood of a rise in earnings outcomes this quarter ($\Delta E_t(+)$) by its prior probability, given past quarterly earnings outcomes (ΔE_{t-1}). From the above, it follows that Bayes' rule infers future sequences of quarterly earning rises, or falls, by mapping past quarterly earnings outcomes into the posterior probability attached to the future ones as follows:

$$Pr_{rise} = \frac{(\Pr[\Delta E_t(+)|\Delta E_{t-1}(+)] \times Pr[\Delta E_{t-1}(+)])}{[\Pr(\Delta E_t(+)|\Delta E_{t-1}(+)) + \Pr(E_t(+)|\Delta E_{t-1}(-)) + \Pr(\Delta E_t(+)|\Delta E_{t-1}(0))]} \dots\dots\dots(4.1)$$

The inferred posterior probability of a rise is simply the probability of a rise in earnings as a proportion of all possible outcomes, be they past rises ($\Delta E_{t-1}(+)$), falls ($\Delta E_{t-1}(-)$), or simply no change in earnings ($\Delta E_{t-1}(0)$).

To illuminate this process, I adopt a simple example from Rabin (2002b) to illustrate the process of a Bayesian updating of expectations. Consider an investor who believes that any of three quarterly earnings change outcomes (i.e. rise, fall or no change) are currently equally likely; $Pr_{rise} = Pr_{fall} = Pr_{no\ change} = \frac{1}{3}$. The investor's unconditional prior is a third for each state. However, that investor also believes that the probability of observing a rise in the current quarter is conditioned on past quarterly earnings changes. So the likelihood of observing an increase in earnings this quarter varies with the previous quarter's reported quarterly earnings change. Assuming that a company whose quarterly earnings fell last quarter is believed by an investor to have a 25% probability of its earnings rising in the next quarter, a company whose earnings remained unchanged in the last quarter is believed to have a 50% chance of earnings rising this quarter, and finally, a company whose earnings rose last quarter is assigned a 75% chance of earnings rising again in the current quarter. Such a set of expectations might be associated with an investor acquainted with stock market investment. Applying the Bayesian revision rule discussed earlier to this case, one will obtain an inferred posterior probability of a sixth of observing a rise in quarterly earnings this quarter given a fall last quarter. This is shown in equation 4.2 below:

$$Pr_{rise|fall} = \frac{1/4}{1/4+1/2+3/4} = \frac{1/4}{1.5} = 1/6 \dots\dots\dots (4.2)$$

Similar reasoning implies a posterior probability of a rise, given no change in earnings last quarter, of a third; $Pr_{rise|no\ change} = \frac{1}{3}$ or $\frac{1/2}{1.5}$. Therefore, the investor's unconditional prior and conditional posterior probabilities after observing a no change outcome last quarter remain unchanged. Finally, a Bayesian infers a posterior probability of a half or $\frac{3/4}{1.5}$, of observing consecutive quarterly earnings rises.

4.3.1.2 Inference about earnings outcomes under the law of small numbers

In the Rabin (2002) model, Freddy, the believer in the law of small numbers, is simply a Bayesian who believes he samples from an urn, or population, that is sampled without replacement in each consecutive period, only to be replenished between the second and third draw. This is simply a formal modelling device employed to mimic the 'overinference' of Freddy, who infers likely patterns where there are none.

In the numerical example used in section 4.3.2 above to illustrate Bayesian revision, there are three states (quarterly earnings rises, falls and no change) and three balls bearing the names of those states drawn on two consecutive occasions. Hence, in my numerical example, the inferred posterior probability of observing a quarterly earnings rise next time, given a fall in the prior quarter, declines from;

$$Pr_{rise|fall} = \frac{1}{6} \text{ to zero, i.e. } \left(\frac{\frac{1-1}{4-1}}{\frac{1-1}{4-1} + \frac{2-1}{4-1} + \frac{3-1}{4-1}} \right) \text{ or } \left(\frac{0}{\frac{0}{3} + \frac{1}{3} + \frac{2}{3}} \right) = \frac{0}{1} = 0,$$

For a company whose earnings did not change last quarter it is:

$$Pr_{rise|no\ change} = \left(\frac{\frac{2-1}{4-1}}{\frac{1-1}{4-1} + \frac{2-1}{4-1} + \frac{4-1}{6-1}} \right) \text{ or } \left(\frac{\frac{1}{3}}{\frac{0}{3} + \frac{1}{3} + \frac{2}{3}} \right) = \frac{1}{3}, \text{ for Freddy (the same as for his Bayesian counterpart), and finally the inferred posterior probability of successive quarterly earnings rises, increases from;}$$

$$Pr_{rise|rise} = \frac{1}{2} \text{ to } \left(\frac{\frac{3-1}{4-1}}{\frac{1-1}{4-1} + \frac{2-1}{4-1} + \frac{3-1}{4-1}} \right) \text{ or } \left(\frac{\frac{2}{3}}{\frac{0}{3} + \frac{1}{3} + \frac{2}{3}} \right) = \frac{2}{3}.$$

The overall impact, therefore, of a believer in the law of small numbers is to shift the distribution of inferred posterior probabilities of earnings rise rightwards. So, from a Bayesian posterior probability of a sixth for rises, following a fall in quarterly earnings, a third for a company recording no earnings change last quarter and, finally, half for consecutive quarterly rises towards an analogous distribution of zero, a third and two-thirds for Freddy. Figure 4.1 graphically represents this rightward shift in posterior probabilities for a Freddy.

This rightward shift depicts Freddy's overinference about future value from the earnings signal he receives.

Freddy's distribution of quarterly earnings change in expectations is skewed to the right of a Bayesian because Freddy puts more weight on the continuations of recent earnings trends (a probability of two-thirds rather than a half) and less weight on reversals of that trend (a probability of zero rather than a sixth). Thus Freddy overinfers earnings trends relative to his rational (Bayesian) counterpart. Charting this overinference will be the central task of the empirical work in this chapter.

The discussion above shows that this model predicts the least investor earnings surprise for extreme momentum cases which Freddy has come to expect over time. In the empirical tests, my focus is on the overinference implication of the Rabin (2002b) model's explanation of momentum. Does the Rabin model illuminate the phenomenon of how an investor's earnings expectations shape price formation in more than just a theoretical sense? Is the impact of earnings momentum primarily observed once a sequence is initiated (i.e. a reversal averted) or primarily as earnings momentum intensifies? I ask what is the value-added of the Rabin (2002b) model in its allowance for the conditioning of sample share returns on the duration of the most recent earnings sequence or, as other researchers have stated (see Loh and Warachka (2012)), does the streakiness of quarterly earnings announcements significantly affect how the stock market responds to them?

4.3.2 Transitions between momentum and reversion regimes in the Barberis *et al* (1998) model

In Rabin's (2002b) model, the representative investor, Freddy, is an imperfect Bayesian in the projection of earnings; however, in Barberis *et al*'s (1998) model, the investor is "always wrong but never in doubt". Therefore, one can safely say that the investor in Barberis *et al*'s (1998) framework is straightforwardly irrational compared to the quasi-rational investor portrayed in the Rabin (2002b) model. In Barberis *et al*'s model, investors believe they are observing an earnings process that switches between eras of trending and mean-reversion. This is despite the fact that in reality earnings always follows a random walk (or at least this is the assumption of the true model in Barberis *et al*). In the Barberis *et al* model, the true earnings-generating process is $E_t = E_{t-1} + y_t$ where y_t is the earnings shock or innovation. In this model, although there is always zero expectation of earnings innovation, investors nevertheless believe that y_t contains a trend in momentum states or a degree of reversal towards no change in mean-reversion states. Hence, while quarterly changes in earnings always follow a random walk and innovations in earnings are always in reality zero in

expectation, investors incorrectly believe themselves to be in one of two states, either mean-reverting or trending (so state, $s = R$ or M). Thus, as one can see, the Barberis *et al* (1998) model makes more spectacular claims about the investor's rationality than the Rabin (2002b) model requires. We might say that for Rabin, investors are irrational, but for Barberis *et al*, investors are delusional, since in BSV's model investors never get to learn the true nature of the earnings-generating process (assumed to be a random walk) and only vary in their self-delusion, sometimes exhibiting a belief in trending and at other times in earnings mean-reversion regimes.

From the model, it is clear that the only difference between momentum and reversion regimes is the degree of confidence attached to observing a continuation or reversion in past earnings innovations, y_t . In the reversion regime of Barberis *et al*'s model, the chance of earnings shocks of the same sign, π_t , is believed to be low (so $\pi_t = \pi_L$ lying between zero and a half, so that $0 < \pi_L < 0.5$) with earnings news being likely to be swiftly reversed. In the momentum regime, the opposite expectation is held by the investor, so that $0.5 < \pi_H < 1$. The contrasting regimes take the form given in table 4.1.

Investors in the Barberis *et al* (1998) model believe that they are either in the momentum or reversion regime in each quarter, despite the fact that quarterly earnings always follow a random walk. Consistent with this self-delusion, investors infer probabilities of leaving states they are in without recourse to any rational set of assumptions. Let λ_R be the probability of leaving the reversion regime, and hence that of entering the momentum regime anew, and λ_M be the probability of leaving the momentum regime and entering the reversion regime in this quarter. Barberis *et al* focus on the case when both λ_R and λ_M are low and hence the quarterly earnings regime rarely changes, although this is not a structural requirement of the model. The transition matrix for switching between reversion and momentum regimes is given by table 4.2.

The central dilemma for the representative investor in this sort of world is to be able to form a best guess of which earnings regime currently prevails. This guess is denoted by q_t , the probability of being in the reversion regime. In reality, earnings always follow a random walk, making this a false or, at best, illusory choice. Regardless of the fact that this decision is simply a false choice, the investor must optimally infer the probability of being in the reversion regime and so see the pattern of announced earnings change direction for the next quarter. The investor's best guess of being in the reversion regime is given by the application of Bayes' rule as follows:

$$q_t = \frac{((1-\lambda_R)X q_{t-1} + \lambda_M X (1-q_{t-1})) X (1-\pi_L)}{((1-\lambda_R) X q_{t-1} + \lambda_M X (1-q_{t-1})) X (1-\pi_L) + (\lambda_R X q_{t-1} + (1-\lambda_M) X (1-q_{t-1})) X (1-\pi_H)} \dots\dots\dots (4.3)$$

Equation 4.3 above represents a case where there is a sequence of opposing quarterly earnings changes, when $q_{t-1} < q_t$, because the observed sequence confirms the investor's (false) belief that he is in a reversion regime.

When quarterly earnings moved in the same direction in this quarter as last, the investor attaches a lower probability to his belief that he is in the reversion regime i.e. $q_{t-1} > q_t$ (i.e., he increases the probability of being in the momentum regime). This is shown in equation 4.4 below:

$$q_t = \frac{((1-\lambda_R) X q_{t-1} + \lambda_M X (1-q_{t-1})) X \pi_L}{((1-\lambda_R) X q_{t-1} + \lambda_M X (1-q_{t-1})) X \pi_L + (\lambda_R X q_{t-1} + (1-\lambda_M) X (1-q_{t-1})) X \pi_H} \dots\dots\dots (4.4)$$

Table 4.3 presents a numerical illustration of the revision process based on table 1 in the original Barberis *et al* (1998) paper. As the number of repeated sequences of improvements occurs ($y > 0$) the probability attached to being in the reversion state declines, and q_t falls for an investor who accords with the constraints of the Barberis *et al* model.

In a similar fashion, repeated alternations of the sign of quarterly earnings changes confirms the representative investor's (false) belief that he is in the reversion regime, thus q_t rises. As the number of repeated sequences of improvements occurs (i.e. when $y > 0$ or $y < 0$), the probability attached to being in the reversion state declines for such an investor.

The particular example considered by Barberis *et al* is when the probability of getting out of the reversion regime (i.e. entering the momentum regime) is low compared to that of leaving the momentum regime (i.e. entering the reversion regime). For the particular numerical example considered in table 4.3, the probability of leaving the reversion regime is both unlikely ($\lambda_R = 10\%$) and three times as low as the probability of leaving the momentum regime ($\lambda_M = 30\%$). In this highly stylised economy, the state is allowed to fluctuate between the momentum and reversion regime at dates 1 to 10 and thereafter enters the momentum regime until the end of the trial at date 14. Between dates 11 and 14, q_t , the investor's inferred posterior probability of being in the reversion regime falls by 5%, reflecting recent consecutive changes in earnings of the same sign. This assumption regarding the updating of q_t is open to exploration, via comparative static exercises, based on inducing variations in the exit state probabilities λ_R and λ_M to alter the predicted behaviour in conformity with the observed data. This variation in the rate of transition can itself be optimally updated and constitutes a degree of freedom available to characterise observed market behaviour not available in the Rabin (2002b) model. Hence, the temporal stability of reversion probabilities becomes a way of differentiating the Barberis *et al* (1998) and Rabin (2002b) models of how earnings momentum persists and impacts upon equity returns. So, Rabin's model focuses

upon the length and intensity of earnings change sequences, but says little about how the probability of reversion is determined. Barberis *et al*'s model explicitly addresses what determines the transition probability between trending and mean-reversion regimes within each regime, but has little to say about variations in the intensity of an investor's response as the earnings sequence lengthens.

One very clear property of Barberis *et al*'s (1998) model is the symmetry of earnings reversion expectations within the trending regime for both quarterly earnings rises and falls. The sign of sequences of EPS changes do not matter; rather, what matters in the Barberis *et al* model is the sequence length. The credibility of this assumption is one way of distinguishing between the empirical values of the two alternative representative agent models of how earnings momentum emerges in the stock market.

4.3.3 Hypothesis development

Behavioural finance theory is built on a number of important concepts which affect human behaviour and financial decision-making processes. The first amongst these concepts are the human cognitive biases and heuristics, and second is the limit to arbitrage. The hypotheses to be tested here are largely based on the first concept – the human decision-making process as influenced by human cognitive biases. The two representative agent earnings momentum models of Barberis *et al* (1998) and Rabin (2002b) offer a number of testable hypotheses on how investors interpret earnings outcomes and how they form their expectations of companies' earnings. The two models draw on the errors made by a representative 'everyman' in arriving at decisions when they are faced with uncertainty about events that have the potential to produce different outcomes.

One particular aspect that is seemingly common amongst the two models above is that there is a systematic component of mispricing which is occasioned by certain factors that cannot be considered as risk factors. These models point to human elements which are both pervasive and persistent in nature as being responsible. In the absence of a 'full information set' for potential investments outcomes, investors are likely to draw on those things they know (albeit wrongly) about a firm's profitability, or otherwise, in arriving at their investment decisions. Several empirical works in finance seem to corroborate this position. A firm's earnings outcome is one of the most powerful fundamentals that provide information about the firm's profitability to the public. It is therefore not surprising that investors, analysts, and other market participants monitor earnings and changes in earnings expectations with such scrutiny. The models of Barberis *et al* (1998) and Rabin (2002b) show that investors observing sequences (streaks) of corporate changes in quarterly earnings outcomes have a

tendency to use the wrong models to predict future earnings outcomes, which subsequently result in incorrect judgements about future stock price for such companies.

The predictions of these two models motivate this empirical investigation of the real-world data. Following the above discussions and the predictions of Barberis *et al* (1998) and Rabin (2002b), I derive a number of testable hypotheses based on inferences drawn from sequences of changes in companies' quarterly earnings realisations by investors. From Rabin's (2002b) model (inference by believers in the law of small numbers), I hypothesise how investors infer (overinfer) the likelihood that short sequences of quarterly earnings changes resemble the long-run rate from which these signals are being drawn. When investors observe short streaks of changes in quarterly earnings outcomes of the same sign, how does this influence their investment decisions?

BSV propose a model in which the representative investor has a mental illusion that a company's earnings are generated by one of two models each quarter. Each of the two models captures the prevailing state of the world and generates earnings accordingly. The earnings trending state switches with the mean-reversion state, with the investor believing that the mean-reversion state is more likely to occur in the next time period. Therefore, the investor believes that he is more likely to see a negative shock in earnings next time period if the current earnings shock is positive, and vice versa. There is therefore a distinct symmetrical distribution of earnings shocks between the trending or mean-reverting state. In contrast, Rabin does not propose any such symmetry in the distribution of earnings shocks. From the foregoing I derive my hypothesis 1 thus:

H₁: There is no symmetry in the distribution of the consistent earnings rises and falls amongst the US S&P500 companies.

This hypothesis follows the theoretical assumption in standard finance that the data-generating process for quarterly earnings is a random process. This implies that innovation in quarterly earnings cannot follow a defined symmetry, as the BSV model seems to suggest. The BSV model suggests a symmetrical distribution where earnings innovation is clearly mapped into trending or mean-reversion regimes. Rabin proposes the behaviour of a representative investor who, although Bayesian (he applies correct prior probabilities in forecasting earnings in period one) falls short of using the correct model to make subsequent forecasts after observing streaks of earnings shocks. Rabin proposes that the behaviour of this investor will depend on the sign of the earnings innovation, the consistency of the earnings innovation, and the length of the streaks of earnings shocks. Furthermore, he proposes that the magnitude and sign of individual (single) earnings shocks attract a less dramatic response from the investor. I derive the next four hypotheses from the above, thus:

H₂: There is no relation between sequences of quarterly EPS falls or rises and the stock market returns.

Hypothesis 2 follows the market efficiency theory that past information about earnings and price cannot predict price. This is because, according to the theory, past information about firms would have been fully incorporated into the price. The theory further claims that any trading strategy based on past public information will not produce abnormal returns. Furthermore, a sequence of quarterly EPS changes is not a known risk factor and should not explain returns. Contrary to this, the Rabin model proposes that if an investor observes sequences of EPS changes, his decision-making process is likely to be impaired by the influence of the gambler's fallacy. This influence will result in future overinference by the investor, ultimately resulting in stock returns trending in the same direction as the sequence of EPS changes.

H₃: There is no difference between the size of average returns generated by sequences of positive and negative EPS changes of equal length.

Hypothesis 3 is based on the market efficiency principle that the average returns following a period of good news and the average returns following bad news are equal. In other words, it is not possible to create a profitable trading strategy that is long (short) on stocks with positive (negative) sequences. However, in reality evidence from momentum studies shows that investors underreact to earnings news: the average realised returns following good news (a positive earnings change confirming a positive sequence of EPS change in the most recent earnings announcement) is greater than realised average returns following bad news (a negative earnings change confirming a negative EPS change in the most recent earnings announcement).

H₄: Investors are not 'surprised' with the increasing length or frequency of the sequence of EPS changes and it has no impact on stock prices.

The Rabin model proposes that the behaviour of the investor who is a believer in the law of small numbers is influenced by the number of consecutive EPS changes he observes. According to the model, in period one, the investor has the same priors as another investor who is fully Bayesian, but his predictions become more extreme than the Bayesian's after observing two and more consecutive EPS changes of the same sign. This hypothesis tests whether there is a difference in the size of average returns generated between sequences of EPS changes of two and higher lengths.

H₅: There is no difference between the response of investors to lengthening sequences of positive and negative EPS changes.

Hypothesis 5 tests whether the behaviour of the investor is the same if he observes growing sequences of positive and negative EPS changes. The hypothesis tests and compares the behaviour of the investors towards companies that have consistent EPS falls versus those that have consistent EPS rises for considerable periods of time. We expect that investors will demand more premia from companies with consistent declines in their quarterly earnings, while companies that consistently post quarterly earnings rises enjoy discounts in their cost of capital. The Rabin model postulates a reversal in returns as the sequences of EPS changes lengthens.

4.4 Main empirical results

4.4.1 Descriptive statistics

Table 4.4 provides the sample descriptive statistics for the variables used. Panel A of table 4.4 shows a summary of the descriptive statistics of the main variables used in this chapter. The mean three-monthly buy-and-hold Fama-French three-factor adjusted return is 0.4% and the median is 0.5%, showing that the distribution is slightly skewed to the left. The three-monthly buy-and-hold abnormal returns exhibit little skewness but strong and significant kurtosis. The mean quarterly EPS for the S&P500 constituent companies is \$1.006 and the standard deviation is approximately 5.99. One point is evident here: although the S&P500 constituent companies are, on average, large firms in terms of their market capitalisation, the size of its companies varies just as much as the size of their quarterly EPS. I exclude a few extremely large changes in quarterly EPS, removing EPS changes exceeding 200%, which seem indicative of error in the I/B/E/S database. In panel A of table 4.4, it is evident that although the average quarterly EPS changes for the S&P500 firms are fairly small and positive, there is very wide variation around that mean value.

Panel B of table 4.4 shows the correlation matrix for the variables. The Pearson (Spearman) correlation between the three-monthly Fama-French three-factor adjusted returns and sequence of quarterly EPS changes (Consistency) is 0.057 (0.064), which confirms the relation between the two in univariate tests. The metric Consistency is the sequence length of quarterly EPS changes and is constructed by using the most recent annualised quarterly earnings change deflated by the prior year end stock price. There is clearly a strong positive Pearson (Spearman) correlation of 0.256 (0.633) between quarterly EPS changes and the length of the quarterly earnings sequence. Both the Pearson and Spearman correlation coefficients show an interesting association between monthly Fama-French three-factor

model adjusted returns (in the months between two adjacent quarterly EPS announcements) and the length of sequence of quarterly EPS changes. The Pearson (Spearman) correlation coefficients between Consistency and the monthly abnormal return (ABR) in the month t when earnings are announced is 0.044 (0.057). The association between them in month $t+1$ is less intense, with a Pearson correlation of 0.012 and a Spearman of 0.024. Their association diminishes even further in month $t+2$ to Pearson = -0.008 and Spearman = 0.007. However, there is a sudden rise in this association in the month of the next EPS announcement. The Pearson (Spearman) correlation coefficient between the monthly abnormal returns and Consistency in month $t+3$ is 0.035 (0.046). This confirms the consensus in the literature that earnings momentum effect in price is most intense around the time of the quarterly EPS announcement. The Pearson (Spearman) correlation coefficient between the sequence of EPS change lengths and monthly cumulative abnormal returns (CAR) is 0.040 (0.052). The CAR is used here as an alternative metric for the buy-and-hold abnormal returns²⁸.

In panels C and D of table 4.4, I break up the distribution of quarterly EPS sequences as each year of the quarterly runs in earnings falls / rises cumulates in my sample data. I calculate the mean, median and skewness of the quarterly EPS changes (Panel C) and Fama-French three-factor model adjusted returns (Panel D). These two measures are matched to their various categories of EPS change sequence lengths, for example, 2 to 4, 5 to 8, and finally 9 to 12 quarters of consecutive falls or rises in EPS. On examination of panels C and D, one characteristic is evident. While quarterly EPS changes are sharply skewed throughout the range of cumulated rises and falls in EPS, this does not reflect in investor returns to holding the stocks which report such strings of cumulative rises and falls in earnings. This suggests that the distributions of quarterly EPS is both skewed and expected to be so by investors. Hence, this may be suggesting that the announcement of lengthening sequences of quarterly EPS rises and falls, or simply more 'streakiness' by sample companies, rarely causes very dramatic movements in their cost of capital.

4.4.2 The distribution of consistent quarterly earnings rises and falls

In this section I conduct the formal test of hypothesis 1. This hypothesis tests the symmetry of the sequences of quarterly EPS rises and falls in my sample data. I begin this analysis by first focusing on figure 4.2, which provides a histogram of the percentage frequency distribution of sequences of quarterly EPS rises and falls in the sample. This same distribution is also presented in panel A of table 4.5 in its numerical form. The asymmetric and uneven distribution of sequences of quarterly EPS changes in the sample is striking.

²⁸ See Dissanaike (1994) for details of various methods for measuring multi-period excess returns.

Interestingly, the sequences of EPS changes in 837 companies show a peculiar distribution pattern, with companies being more likely to report extreme positive quarterly increases. A Shapiro-Wilk test of normality (reported in panel B of table 4.5) rejects the hypothesis that the Consistency variable is normally distributed, with a t-statistic $V = 120.88$ ($\text{Prob} > z = 0.00$). More than 21% of the time, companies consistently post positive EPS change increases for a period of three years, as against a little over 1% that consistently post declining quarterly EPS changes for a period of twelve quarters. This affirms a long-held belief in market-based accounting research on meeting and beating the earnings targets and the requisite earnings management to do just that (see Bartov *et al* (2002)). It also reflects the fact that consistently poorly performing companies do not enter the S&P500, and if they do, they are not likely to be in it for long. About 13% of the companies report one quarter of EPS rises before reporting a decline in the following quarter. For companies that report differing lengths of positive EPS rises, there is a clear trend of a steady decline in the number of companies reporting consistent quarterly earnings rises, from 13% for one quarter to 2% for eleven quarters. There is also a sudden increase in the number of companies that report consistent quarterly EPS rises for twelve quarters. On the other hand, there is no such discernible pattern in the number of companies that report consistent falls in quarterly EPS. Although there are no companies that report just one quarter of decrease in quarterly EPS change, there is a decreasing number of companies that report a consistent number of declining EPS changes from two successive to five successive quarters. Beyond this point, there is no particular pattern for companies reporting successive declines in quarterly EPS changes from six to twelve consecutive quarters. The low number of companies that post declining quarterly EPS changes for twelve consecutive quarters is understandable. Firms reporting declining quarterly EPS for long periods of time run the risk of going from declining earnings to making losses and subsequent bankruptcy.

In figure 4.3, the histogram shows the distribution frequencies of positive and negative quarterly EPS change reported by the companies over twelve quarters. More than 61% of the companies post small increase or decrease in EPS changes which cluster around the zero point. A little less than 1% of the companies report a quarterly EPS change decline of 100% from the previous quarter, while a little above 1% report a quarterly EPS change increase of 100%. In all, it is clear that companies report positive quarterly EPS changes more often than they report negative changes. A good number of research works look at the symmetry of quarterly EPS change distribution. Some look at the link between this and the levels of quarterly EPS that firms report, while others try to interpret it in terms of EPS management to exceed thresholds. Although the distribution of the EPS changes of my sample companies seems to suggest confirmation of this research, it is hard to say that with

certainty. Beaver *et al* (2007) support Durtshi and Easton's (2005) argument (see also Burgstahler and Dichev (1997)). The authors posit that the discontinuity in the distribution of price-deflated EPS changes is largely driven by the same factors that cause discontinuity in the distribution of price-deflated EPS levels. Beaver *et al* (2007) assert that the term 'discontinuity' is shorthand for an unusually low frequency of small loss observations and an unusually high frequency of small profit observations, relative to the frequencies in the adjacent intervals of earnings distribution. It does not imply that the cumulative distribution function is discontinuous at zero. In line with Beaver *et al* (2007), my sample data show a high frequency of small positive quarterly EPS changes relative to small negative quarterly EPS changes, even when quarterly EPS changes are deflated by the prior year end stock price. Hence, it is important to show that the asymmetry in the distribution of quarterly EPS changes does not support the kind of symmetry between EPS rises and falls that the BSV model proposes.

Figure 4.4 plots the mean quarterly EPS changes over twelve quarters of consistent quarterly EPS rises and falls. The cumulatively larger nature of repeated falls in quarterly EPS is very clear from the data, while the scale of repeated quarterly EPS rises stabilise to smallish values after a year. Consistent quarterly declines seem to accumulate fairly alarmingly, while consistent quarterly EPS growth appears to be a fairly stable, possibly even manageable, form of earnings smoothing in my sample data.

4.4.3 Consistent earnings rises and falls and the stock market response

The basic pattern in figure 4.4 showing that the cumulative quarterly EPS falls are becoming more dramatic in scale, while cumulative quarterly EPS rises stabilise to small values is confirmed by figure 4.5. This suggests that the pattern does not result from a few rogue outlier observations that would imply that there is no broader trend in the data. Given this stylised fact, one would conclude that it is most probably not wise to pool all consistent quarterly earnings rises and falls into the same two states as the BSV (1998) models does. This is because the requisite symmetry this sort of model implies is not present in my data sample (see table 4.4 for the distribution of sequences of quarterly EPS rises and falls). Furthermore, the cumulative impact of quarterly EPS falls is far more dramatic than the cumulative impact of quarterly EPS rises. Additionally, consistent quarterly EPS rises, which continue for twelve quarters, are common, constituting about almost a quarter of my sample data. This is unlikely to have a dramatic stock market impact because something that quarter of stocks do is hardly shocking news to investors. Figure 4.6 reconstructs figure 4.5 using the median of the Fama-French three-factor adjusted returns rather than the mean Fama-

French three-factor adjusted returns to guard against my inferences being driven by a minority of rogue data points.

In figure 4.5 I show how more extreme sequences of quarterly EPS changes are reflected in investor returns. In this figure, I plot the mean buy-and-hold returns (adjusted by the Fama-French three-factor) in the three months following the reported quarterly EPS change for increasing durations of quarterly EPS rises and falls over a twelve-quarter period. This shows again that the average market response to successive EPS changes is highly uneven across different durations of consistent quarterly EPS rises and falls. For consistent quarterly EPS rises, the market response is always small and positive, with little increase in the intensity of this response as the run of positive EPS changes lengthens. This suggests some degree of learning about the scale and direction of the sequences of quarterly EPS changes that is more consistent with the Rabin (2002b) model than the Barberis *et al* (1998) model. The market response amongst investors to consistent quarterly EPS falls is far more uneven, with no real discernible trend being present here. This makes sense, because quarterly EPS falls, especially large cumulative ones, are by their very nature transitory. This is because companies with consistent large EPS falls will either correct the negative trend and return to better form or face liquidation once the EPS falls become large earnings losses. Companies with declining quarterly EPS over a long period must offer a high rate of return to compensate the investors for the risk of holding their stocks if they are to survive. From figure 4.5, such compensation (premium) is fairly clear for the most extreme consistent group of earnings fallers, but fairly ephemeral, if at all present, for companies reporting only eight or fewer quarters of earnings falls. Such shorter temporary dips in earnings performances are not apparently accompanied by the company having its cost of equity capital raised by the stock market.

Figure 4.6 confirms the asymmetric market responses to quarterly EPS rises and falls using the median buy-and-hold Fama-French three-factor model adjusted returns performance metric over a three-month period following the quarterly earnings announcement. In this alternative test, the payment of premium returns in order to compensate for the risk of repeated losses clearly shows. And again, as in the case of the plot against average returns; companies reporting repeated earnings falls for a period of less than eight quarters display no discernible pattern in the cost of the equity capital they are required to pay.

In panels C and D of table 4.4, I break up the distribution of sequences of EPS changes as each year of the quarterly run in earnings changes cumulate. Then the mean, median and skewness of the of quarterly EPS changes (shown in panel C) and Fama-French three-factor adjusted returns performance metric (shown in panel D) for 1 to 4, 5 to 8, and finally 9 to 12

quarters of consecutive falls and rises in EPS (each successive year of consecutive rises and falls shown in panel B) are calculated.

From the distribution shown in this table, one characteristic of the data is very clear: while quarterly EPS changes are sharply skewed throughout the range of cumulated rises and falls in EPS, this is not reflected in investor returns to holding the stocks which report such streaks of cumulative rises and falls in earnings. This suggests that the distribution of EPS changes is both skewed and expected to be so by investors. Hence, the announcement of lengthening EPS rises and falls sequences by sample companies rarely causes very dramatic movements in their cost of capital. Therefore, it appears only substantial 'streakiness' in earnings is priced in my S&P500 sample frame.

4.4.4 Regression-based results

Here in the regression-based analysis, I test hypotheses 2 to 5 enumerated in section 4.3.5 above.

4.4.4.1 Sequences of quarterly EPS changes and monthly stock abnormal returns

Here I conduct regression analysis to test my hypothesis 2. This hypothesis tests the relation between sequences of quarterly EPS changes and market returns. The first set of regression results presented in table 4.6 clearly shows evidence of earnings momentum in the monthly Fama-French three-factor adjusted returns as explained by the sequence of EPS changes. In each of the three months in any particular quarter, earnings momentum achieves its highest intensity in the same month (month t) that earnings are announced. The earnings momentum effect continues in the month immediately following the month that earnings were announced but with less intensity. This trend continues in the second month, but earnings momentum becomes weaker than in the month earnings were announced, with the monthly abnormal return even turning negative by the third month. However, there is a reversal of trend and a dramatic positive increase in the earnings momentum effect in the following month. This month coincides with the month in which the next quarterly earnings news is reported. These findings are consistent with the underreaction anomaly documented in the literature. This anomaly, which was initially documented in the United States markets and later in other markets around the world, seems to suggest that investors fail to fully understand the information contained in current earnings outcomes with respect to its implications for future earnings realisations. The monotonic decline in the monthly adjusted returns, following the month in which the earnings announcement was made appears to show that as time passes and more information about earnings filters into the market, investors adjust their predictions about future earnings in line with the most recent

information. However, as seen here in table 4.6, there is a sharp rise in abnormal returns around the following month when the new quarterly EPS figure is announced compared to the month immediately before. One way to explain this jump is that investors still fail to fully understand the implications of earnings in the previous quarter for the current month's price. This behaviour is also consistent with the slow diffusion of quarterly earnings information into price. This hypothesis suggests that information about earnings slowly filters into price, and this process continues until there is full price discovery. Several research studies report this pattern of behaviour in the literature, for example Liu *et al* (2003) report this behaviour for the UK markets.

In table 4.6, the interaction term constructed from the sequences of quarterly EPS change and annualised quarterly EPS change predicts a monotonically positive increase in monthly Fama-French three-factor adjusted abnormal returns from the earnings announcement month up until the month before the next earnings announcement. This suggests that positive change in the annualised quarterly EPS reinforces the predictive power of the sequence of quarterly EPS change. This also suggests that positive change in EPS increases the overinference by the investor of the possibility of future prosperity for the company in question. This obviously pushes up the future prices of the company's stock.

4.4.4.2 The impact of sequences of quarterly EPS changes on three-month buy-and-hold abnormal returns

In this section I continue to test hypothesis 2 by using three-month buy-and-hold abnormal returns in place of monthly abnormal returns. I undertake regression-based tests to establish whether the variable Consistency impacts upon the amount of earnings-generated momentum in price. Here, I employ buy-and-hold returns, adjusted by the Fama-French three-factor, covering a three-month period following the announcement of the most recent quarterly earnings change as my dependent variable. I present the results of this regression analysis in table 4.7. The table shows the results of a basic regression of quarterly EPS changes on their matched three-month buy-and-hold Fama-French three-factor adjusted returns. It is evident that the market responds to quarterly earnings rises and falls as a sequence of EPS changes lengthens. The Consistency variable explains 0.05% of the abnormal returns, which is statistically significant with $t\text{-value} = 8.77$ at a 99% confidence level. It is already shown in section 4.4.2 from the graphical analysis that while the market responses to lengthy sequences of quarterly EPS rises are pretty stable, the stock market response to lengthy declines in quarterly EPS is more erratic. Specifically, it appears that companies reporting a long stream of quarterly EPS falls are forced to pay a premium for risk to their remaining long-suffering investors. In the regression-based test, this is reflected

by the strongly significant positive coefficient on the Consistency variable, which measures the length of the sequence. This premium payment is especially marked in the longest earnings fall sequences, say after eight quarters of consistent earnings declines. The low R^2 of 5% to 6% in reported regressions in table 4.7 attests to the difficulty of exploiting the empirical regularities in earnings outcomes and their sequences to earn returns in excess of the Fama-French three-factor model benchmark. The proportional relation between the reported R^2 of the regression and an F-test for its overall explanatory power suggest that these regularities, while present, are masked by substantial random variation as envisaged by the efficient market hypothesis²⁹. So, while the regression results here seem to offer arbitrage opportunities, they are certainly not riskless, even after controlling for the risk factors modelled in the standard Fama-French three-factor model benchmark. In the multivariate regression of Consistency and DeltaEPS (most recent quarterly EPS change), the DeltaEPS variable loses its explanatory power on the buy-and-hold abnormal returns. DeltaEPS explains on 0.005% of the abnormal returns which is not statistically significant. One reason that seems plausible for this observation is that within the S&P500 constituent companies, it is very likely that any observed short-term earnings-generated momentum will very likely be arbitrated away in such a large and liquid market.

4.4.4.3 The impact of differing quarterly EPS sequence lengths on stock returns

This section presents tests to show the impact of various lengths of sequences of EPS change on Fama-French adjusted returns. Panel A of table 4.8 shows the regression results of differing market responses to lengthy quarterly EPS rises and falls of more than eight quarters. The rationale behind this is to examine the impact that the growing length of a sequence of EPS changes of a particular sign may have on price. This section also tests whether there is a significant difference in returns between companies reporting consistent EPS rises and those reporting consistent EPS falls. In addition, this section tests how 'surprised' investors are if there is a growing 'streakiness' in the EPS change. The section in effect tests hypotheses 3, 4, and 5.

In this regression, I allow the regression intercepts to shift depending on the nature of the quarterly EPS sequence. This allows me to condition on both the length and sign of earnings sequences. I include a dummy variable in the regression for the quarterly EPS sequence being a sequence of over eight quarters of either EPS change rises or falls, denoted as *More2yearpos* and *More2yearneg* respectively. A further dummy variable to capture quarterly earnings rises regardless of duration is denoted as variants of 'Rise' (1..., 4) in my regressions. The year of the quarterly EPS change is also included in the regression as a

²⁹ See Gujarati (2004).

control variable, to capture any temporal instability in the regression model. Although the market response to quarterly EPS changes is strongly affected by the year in which they occur, with price responses being more muted as the years go by, there seems to be little difference in the average market response to quarterly EPS rises and falls. Companies reporting consistent quarterly EPS rises for more than eight quarters earn significant negative three-month buy-and-hold Fama-French three-factor adjusted returns of -0.50% (t-value = -2.43). On the other hand, companies that post consistent quarterly EPS falls for over eight quarters earn significant positive three-month buy-and-hold Fama-French three-factor adjusted returns of 1.16% (t-value = 4.02).

While the lengthening sequences of EPS rises and falls differ little in their average response from the market, a separation in response becomes clearly evident at the extremes of the earnings sequence distribution. Those companies with prolonged quarterly EPS falls pay a premium to investors who remain with them, presumably as compensation for the risk of the company failing, while companies reporting consistent quarterly earnings growth enjoy a small discount on their cost of capital. These premia and discounts seen in my results are not explained by the standard risk proxies embedded in the Fama-French three-factor model.

Panel B of table 4.8 presents the results of a regression with another two dummy variables. One of the dummy variables, denoted as *Less2yearpos*, represents earnings rises of up to eight quarters. The regression shows that for a unit increase in length, there is an increase in three-month buy-and-hold Fama-French three-factor adjusted returns of 0.50% (t-value = 2.68). On the other hand, for the second dummy variable, denoted *Less2yearneg*, representing earnings falls of up to eight quarters, there is a more dramatic loss of -1.20% (t-value = -4.02) in three-month buy-and-hold Fama-French three-factor adjusted returns for a unit increase in the length of the *Less2yearneg* sequence.

In panel C of table 4.8, I include two dummy variables in the model to capture the impact of different lengths of EPS rises and falls (of between one and four quarters in length) on the abnormal returns. This test further examines whether the duration of a sequence has any effect on the size and sign of abnormal returns. The dummy variable *Less1yearpos* denotes EPS rises of one to four quarters, while *Less1yearneg* is a dummy that represents EPS falls of one to four quarters. A panel regression of these two variables with the *Consistency* and *DeltaEPS* variables as control variables shows an interesting pattern. For consistent EPS rises of one quarter and up to four quarters; with each unit increase in the length of the sequence, there is a decrease of -0.56% (t-value = -3.04) in the realised three-month buy-and-hold Fama-French three-factor adjusted returns. This is both economically and

statistically significant at a 5% confidence level. However, for consistent EPS falls of one to four quarters, a unit increase in the length of EPS sequence results in a small decrease of -0.14% (t-value = -0.80) in the three-month buy-and-hold Fama-French three-factor adjusted returns. This coefficient is not significant at the 5% confidence level.

The results from the two dummy variables, *Less1yearneg* and *Less2yearneg*, representing EPS falls of up to four and eight quarters respectively, show an interesting, consistent pattern of behaviour. Companies reporting consistent quarterly EPS falls for four quarters earn small negative three-month buy-and-hold Fama-French three-factor adjusted returns of -0.14%. However, for those companies that continue to post declining EPS for about eight quarters, their stocks earn even more negative three-month buy-and-hold Fama-French three-factor adjusted returns of -1.20%. The investors here may be holding on to such stocks with the hope that the companies will turn their earnings around and hence their stocks will earn better returns in the future, or the stocks may simply be very illiquid, with few buyers left. This is consistent with a phenomenon known in behavioural finance as the 'disposition effect', which occurs when investors are reluctant to sell shares that are falling in value relative to the ones whose values are rising. A correspondingly interesting pattern is shown by companies posting different durations of quarterly EPS rises. Those firms that post consistent EPS rises for four quarters earn a negative three-month buy-and-hold Fama-French three-factor adjusted return of -0.56%. The abnormal returns become positive and increase to 0.50% if firms continue to post EPS rises for up to eight quarters. The investors' response to the differing lengths of EPS rises suggests that investors do think that after a few positive earnings surprises, the quarterly EPS will soon revert on a "what goes up, comes down" basis. Thus, the negative abnormal returns after four quarters turn positive after eight quarters of consistent EPS rises. The investors' response to both the lengthening EPS rises and falls is consistent with the earnings momentum literature.

For both EPS falls and rises of four- and eight-quarter duration, there is clearly a differing response from investors, although from the histogram in figure 4.5, it is evident that there is a positive, albeit minimal, increment in monthly buy-and-hold abnormal returns for EPS rises of one, two, three, and four quarters. The average response of the monthly buy-and-hold abnormal returns to EPS rises for the four quarters is negative. For sequences of earnings rises of up to eight quarters, though, there is a positive and significant response to the lengthening sequence of EPS rises. The response of three-month buy-and-hold Fama-French three-factor adjusted returns seems to reverse between EPS rises of four and eight quarters. This is completely different from the response of three-month buy-and-hold Fama-French three-factor adjusted returns to an emerging sequence of EPS falls of four and eight quarters' duration. For sequences of EPS falls of four quarters, the three-month buy-and-

hold abnormal return is negative and not significant at the 5% confidence level. However, up to eight quarters of consistent EPS falls, the abnormal returns are strongly negative and significant. There seems to be disposition effect at play here, although it is hard to say for certain.

From the three consistent EPS durations results above, it is evident that as the year dummy of EPS change lengthens, the three-month buy-and-hold abnormal returns become more muted and negative. With the dummy variable Rise (of various variants), the mean three-month buy-and-hold abnormal return is negative (except in cases where the duration of sequence of EPS changes is four quarters or less) for all companies posting consistent EPS rises in my data sample, which might imply market anticipation of an oncoming end to the sequence.

From table 4.6, the interaction term's (Consis* Δ EPS) impact on the abnormal returns increases in the month following earnings announcement but starts to decline in the third month. However, it has a negative impact on the consistency variable with three-month buy-and-hold abnormal returns declining from 0.05% to 0.04% as shown in table 4.7. These results suggest that although the consistency variable is the main explanatory variable for earnings momentum, the quarterly earnings changes on its own has an attenuating effect on the investors' response to lengthening sequences of quarterly EPS changes in a three-month buy-and-hold investment strategy. This is consistent with evidence from other studies which shows that quarterly EPS change in the most recent earnings announcement explains earnings momentum in stock returns although it has a weaker explanatory power in the presence of the consistency variable. The interaction term above is the product of consistency variable and the quarterly EPS changes.

4.5 Additional tests for robustness checks

In the following sub-sections I present the results of four additional tests to confirm the robustness of the primary results presented in section 4.4. This is achieved by employing event clustering analysis, an alternative estimation method, and one alternative specification for the main estimation equation.

4.5.1 Sub-period analyses

In order to examine whether the results of the analysis in the previous sections are confined to a particular period in the sample data, I provide sub-period analyses in this section. The sample data is divided into two equal periods for analysis: from January 1991 to December 1998 and from January 1999 to December 2006. In panels A, B, C, and D of table 4.9, I

present the results of this sub-period analysis. The performance of the different explanatory variables follows the same pattern as shown in the full period analyses in section 4.4 above.

It is interesting to see that even in both sub-period analyses; companies posting declining quarterly EPS beyond eight quarters seem to pay a premium to investors who patiently continue to hold their shares. Although this remains the case in both sub-periods, comparing this in the two sub-periods, a higher premium was paid to investors holding the shares of companies that consistently post declining quarterly EPS for more than eight quarters in the period 1991 to 1998 (1.30% three-month buy-and-hold abnormal returns) as against (0.90% three-month buy-and-hold abnormal returns) in the period 1999 to 2006. This is shown in panels C and D of table 4.9 respectively. One way to explain the different premia earned in the sub-periods may be to look at the impact of the numerous economic and financial market shocks that characterised the early and mid-1990s. This could also be attributed to the rapid EPS growth in US companies in the 1990s (the average annual EPS growth in the US in the 1990s was 15%). Companies posting quarterly EPS rises consistently for more than eight quarters seem to enjoy some discount, as are the case in the full period analysis. This can be seen as a reversal of trend, as previously these firms are paying increasing premia for consistent quarterly EPS rises posted up until the eighth quarter. Another way to explain this could be that investors have now realised the apparent earnings management which might be going on in those companies and decide to invest otherwise. There is also the possibility that the impact of regulation fair disclosure (Regulation FD 2000) in the United States might have helped to facilitate this³⁰. Investors are no longer 'surprised' by the incremental rise in these companies' quarterly EPS after many quarters and now begin to desert their stocks. It is obvious from this that the length (or the duration) of consistent EPS rises/falls is crucial in determining the earnings momentum effect on stock prices. There is, however, a small positive three-month buy-and-hold abnormal return (0.002%), albeit not statistically significant, earned by investors holding shares of companies that consistently post quarterly EPS rises for more than eight quarters in the sub-period of 1999 to 2006, as against much more negative abnormal returns of -0.95% in three-month buy-and-hold abnormal returns in the sub-period of 1991 to 1998. For companies posting consistent EPS rises, there is a positive, not significant (0.23%), relation between quarterly EPS rises and the three-month buy-and-hold abnormal returns in the sub-period 1999 to 2006. However, this relation is negative (-0.68%) and statistically significant in the sub-period 1991 to 1998. The stocks of companies posting positive change in quarterly EPS earn positive buy-and-hold abnormal returns on average. This is consistent with previous research; stocks usually show abnormal returns in the same direction as the quarterly earnings surprise.

³⁰ See Mohanram and Sunder (2006).

The sub-period analysis for the impact of sequences of EPS on abnormal returns shows that the results of the full period analyses are not confined to a particular period. On the average, the sequence of quarterly EPS change is positive and statistically significant in the month in which the EPS is announced and not statistically significant in the next two months following the announcement. This is the case in both the sub-periods of 1991 to 1998 and 1999 to 2006, as shown in panel C and D of table 4.9. This is exactly the same findings as for the full period analyses.

4.5.2 Analysis of data by industry classification

There are times when industry clustering may occur, and this means that regression results are likely to be driven by some industry sectors within the sample data of interest³¹. The problem posed by industry clustering cannot be ignored, as several researches have shown that this problem reduces the power of statistical tests in testing for the significance of abnormal returns (Dyckman *et al* (1984); Mackinlay (1997)). Dyckman *et al* (1984) observe that although researchers who study securities assume that securities are usually selected through random sampling, event studies do not usually involve random samples. The authors posit that accounting events are often clustered around particular industries, time periods, or both. Brown and Warner (1980) examine time clustering in monthly returns. They posit that clustering impacts and lowers the number of securities whose month '0' behaviour is independent, and consequently, if there is positive correlation across securities' mean historical returns in calendar times, clustering will increase the variance of performance measures and hence lower the power of the tests. Although my sample's descriptive analysis does not indicate a significant degree of industry clustering, I still test to confirm that the initial findings are not driven by industry effect.

To investigate industry clustering, I select ten sector groupings according to Standard and Poor's global industry classification standard (henceforth the GICS code). Each of the ten sector groupings is present in my S&P500 constituent companies of my sample data. The ten sector groupings are: Energy (10), Materials (15), Industrials (20), Consumer discretionary (25), Consumer staples (30), Health Care (35), Financials (40), Information technology (45), Telecommunication services (50), and Utilities (55) – the sector codes are in parenthesis. The first step here is identifying and matching each of the companies in my sample data with its S&P500 GICS code, defined according to the two-digit GICS code provided by S&P.

³¹ See Moskowitz and Grinblatt (1999).

The regression results of the industry sectors are summarised in table 4.10. The results are consistent with the initial findings of the analyses in section 4.4. In eight of the ten sectors analysed, on average, the sequence of quarterly EPS changes has a positive impact on the Fama-French adjusted returns, although this is quite muted in a few of these sectors. On examining the impact of different durations of sequences of EPS rises or falls in the different sectors, I observe the same trend shown earlier in the main analyses. For companies with sequences of quarterly EPS rises of more than eight quarters, the monthly buy-and-hold abnormal returns are negative in eight of the ten sector groupings, while for companies posting EPS falls of over eight quarters, the monthly buy-and-hold abnormal returns are positive in nine of the ten sector groupings. These results are consistent with the results obtained earlier from the main regression analyses which show that companies that post EPS falls for over eight quarters seem to pay a premium to their long-suffering investors who hold onto their stocks, disregarding the fact earnings have consistently declined for many quarters, whereas companies that post consistent EPS rises for more than eight quarters enjoy a corresponding discount in their cost of capital. For companies posting consistent EPS rises and falls for a shorter period of four quarters and eight quarters, the impact on their monthly abnormal returns follow the same trend seen in the main regression analyses. The results here show that the findings in the results of the main analyses are not driven by clustering around few industry sectors but are widespread throughout the entire sample data.

4.5.3 Earnings momentum and information discreteness

In this section, I introduce the information discreteness metric as modelled by Da *et al* (2014) to test the extent to which the impact of information discreteness exacerbating earnings momentum in my sample data. Da *et al* (2014) describe information discreteness as both the rate with which information about firms arrives in the market and the magnitude of each signal that is received by the market. The authors distinguish the impact of small amounts of information which continuously flow into the market from that of large pieces of information that come at discrete time periods. Although I do not test the frog in the pan hypothesis of Da *et al* (2014), I test the impact of earnings information discreteness (arrival of earnings news) on earnings momentum in returns. It is well known that conjectures about earnings are one source of value-relevant information, usually conveyed by analysts' forecasts of earnings and speculation in brokers' reports. The descriptive statistics presented in table 4.4 confirm that the sample displays a skewed distribution of company returns, which implies that the results may be sensitive to how quickly the market receives and processes information about sample companies' performance. A less skewed distribution of returns indicates that earnings information flows into price in a much timelier manner. Hence, I

introduced the information discreteness metric as a control variable into the original regression equation alongside length of EPS sequences to determine its impact on the earnings momentum observed in my data sample. The information discreteness metric is constructed following Da *et al*'s (2014) approach. Information discreteness ID_z is defined as:

$$ID_z = sgn(PRET) \cdot \frac{[\%neg - \%pos]}{[\%neg + \%pos]} \dots\dots\dots (4.5)$$

where %neg and %pos are the percentage of days during the portfolio formation period with negative and positive returns respectively, PRET is a company's cumulative return over the past twelve months excluding the most recent month, $sgn(PRET)$ is the sign of PRET and is equal to +1 when PRET is positive and equal to -1 when PRET is negative (Da *et al* (2014)). The information discreteness measure does not depend on the size or magnitude of a stock's returns but rather on the sign of the return (this is despite the fact that it is derived from PRET, which depends on the size of cumulative returns). This property differentiates this metric from return volatility, skewness and kurtosis. Furthermore, the information discreteness proxy defines the time series property of the PRET as seen in the daily returns from which the cumulative formation period returns are calculated³².

I include a dummy variable, ID_z , to my original model to test for the impact of information discreteness or granularity upon the earnings momentum seen in my sample data. The dummy ID_z takes a value of one when information discreteness is above its median value, or granular, and zero otherwise (when smooth). The distribution of informational discreteness as captured by the ID_z metric is skewed left in the sample by a few companies with very smooth continuous price movements, causing the mean to lie at 0.07 while the median is 0.053. This dummy is constructed on an individual company basis, hence it allows for the control of shifts in company intercepts (but not annual) with the degree of recorded information discreteness.

The results of this regression are presented in table 4.11. The dummy is significant, suggesting that information discreteness is indeed a factor that helps in fomenting earnings momentum as well as price momentum in stock returns. As I indicated above, I did not test the Da *et al* (2014) frog in the pan hypothesis; however informational discreteness is clearly one factor determining the intensity of earnings momentum, even after controlling for the consistency of earnings sequences. However, it is important to point out that the inclusion of such a control for informational discreteness in the tests does not appear to weaken the role of a consistent streak of quarterly EPS rises and falls in determining the extent of the

³² See Da *et al* (2014) for details of how PRET is measured.

earnings-driven momentum observed in the data. So earnings streakiness and informational discreteness appear to have separate and additive effects in driving the momentum in stock price.

4.5.4 Profitability of earnings momentum strategies with different duration of EPS rise or fall sequence employing Bayesian estimation method

The ordinary least squares regressions (panel regressions) focus on the average impact of EPS changes and their sequence lengths given symmetry with the assumption that investors sample from a fixed known normal distribution of EPS changes and earnings sequence lengths. But as the representative agent models outlined in section 4.3 emphasise, investors do not know the true distribution of EPS changes or the duration of each consistent earnings change sequence. Investors must learn these distributions by trial and error. The Bayesian estimates of the key model coefficients capture this process of price discovery. For a normal distribution, the ordinary least squares estimation has all the attractions of a maximum likelihood, providing parameter values that make the sample data most likely to be observed. However, this type of estimator leaves open many theories which attach a probability of one (the greatest possible likelihood) to factors which could not conceivably play any causal role in driving the phenomenon in question. In this sense, maximum likelihood estimators explain too much variation in the data compared to their Bayesian counterparts³³.

The regression results presented in tables 4.7 and 4.8 are based on minimising squared deviations from the mean. Table 4.12 provides Bayesian estimates of the main regression results. The results in table 4.12 show a weighted average of the investor's prior distribution of the parameters and their sample means. The weight of the sample means increase as the estimation sample grows. Initially, the sample weight placed on the various independent variables (e.g. Δeps , consistency, and consistency \times Δeps) is set to zero. This is consistent with the investor's scepticism about the ability of fundamentals to explain abnormal returns. The results presented in table 4.12 show regression coefficients estimated at the 5%, 50% and 95% points of distribution of three-monthly buy-and-hold Fama-French three-factor model adjusted returns. The explanatory powers of the consistency variable and the interaction term increased monotonically as the distribution of BHAR increased from 5% through to 95%. This shows that investors make upward adjustment in the valuation model when they observe growing sequences of quarterly EPS changes. This result reveals the scale of variation in estimated regression coefficients and also confirms that the results of the regression are robust to shifts in the estimated mean.

³³ See Howson and Urbach 2006, p. 215 – 216.

4.6 Summary and conclusion

In this chapter, I present evidence on the suitability for empirical application of the two representative agent style models of the stock market impact of momentum in reported earnings. The early evidence that is shown in the results leads one to favour the Rabin (2002b) model based on the 'law of small numbers' as against the Barberis *et al* (1998) model of investor sentiment. Two very important reasons lead to this conclusion. First, the results do not seem to support the BSV model's assumption that investors never infer the true nature of the quarterly earnings process they face. Contrary to this BSV model assumption, the investors seem to show that some kind of learning is going on through the growing sequence of EPS at every earnings announcement. The second reason is the simplicity of the distinction between the trending and mean-reverting regimes in the BSV model without regard to the length of each sequence that prevails. The results of the empirical analyses carried out in this chapter suggest that it is both the duration of the quarterly EPS change sequence and its sign which primarily determine their impact on prices, rather than consistent earnings rises as such. Prolonged sequences of quarterly EPS falls seem particularly marked in exerting a risk premium from US S&P500 constituent companies in my chosen sample period. Only the Rabin (2002b) model allows for effective modelling of the impact of extensive falls in quarterly earnings, since it does not impose the symmetry in response to quarterly EPS rises and falls which the Barberis *et al* (1998) model requires.

Table 4.1
Momentum and Reversion regimes in the Barberis *et al* (1998) model

The tables below show the reversion and momentum models of Barberis *et al* (1998). π_L is the low probability ($0 \leq \pi_L \leq 0.5$) attached to any given shock being repeated in terms of its sign in the next time period within the reversion regime in panel A and π_H is the high probability ($0.5 \leq \pi_H \leq 1.0$) attached to a shock of any given sign being repeated within the momentum regime. The key aspect of this model lies in the fact that π_L is small and π_H is large. This means that under the mean-reverting regime, a positive shock is likely to be followed by a negative shock, while under the momentum regime; a positive shock is likely to be followed by another positive shock.

Panel A

Reversion Regime	$y_{t+1} = y$	$y_{t+1} = -y$
$y_t = y$	π_L	$1 - \pi_L$
$y_t = -y$	$1 - \pi_L$	π_L

Panel B

Momentum Regime	$y_{t+1} = y$	$y_{t+1} = -y$
$y_t = y$	π_H	$1 - \pi_H$
$y_t = -y$	$1 - \pi_H$	π_H

Table 4.2

The transition matrix from the reversion to the momentum regimes and back

Table 4.2 shows the transition models in the Barberis *et al* (1998) model, transiting from reversion to momentum and back to reversion. λ_R is the probability of leaving the reversion regime and λ_M is the probability of leaving the momentum regime. The parameters λ_R and λ_M are responsible for determining the transition probabilities from the reversion regime to the momentum regime respectively. The model focuses on small λ_R and λ_M , which implies that transitions between reversion and momentum regimes occur rarely.

Prevailing regime	In Reversion Regime next quarter	In Momentum Regime next quarter
Reversion	$1 - \lambda_R$	λ_R
Momentum	λ_M	$1 - \lambda_M$

Table 4.3

Earnings expectations in the Barberis *et al* (1998) model

Table 4.3 below is based on an illustrative simulation of the model presented in Barberis *et al* (1998) table 1 in which $\pi_L = \frac{1}{3}, \pi_H = \frac{3}{4}$ and $\lambda_R = 0.1, \lambda_M = 0.3$. $q(t)$ represents the probability that the mean-reverting model is generating quarterly earnings y_t .

Date (t)	q(t)	y_t	Length of run
0	0.50	y	0
1	0.80	-y	0
2	0.86	y	0
3	0.88	-y	0
4	0.88	y	0
5	0.84	y	1
6	0.87	-y	0
7	0.83	-y	1
8	0.87	y	0
9	0.88	-y	0
10	0.88	y	0
11	0.84	y	1
12	0.81	y	2
13	0.80	y	3
14	0.77	y	4

Table 4.4: Summary of descriptive statistics for sample data

Panel A shows the descriptive statistics of the sample and Panel B the correlation matrix of all the variables used in analysis in this chapter. The statistics include the number of observations of each of the variables, average value, median, standard deviation, minimum and maximum value, skewness and kurtosis respectively. The variables presented are the stock's three-month buy-and-hold Fama-French three-factor model adjusted returns (BHAR), three-month Fama-French three-factor model adjusted cumulative returns (CAR), quarterly earnings-per-share levels (EPS), annualised quarterly earnings-per-share change (Δ EPS), annualised quarterly earnings-per-share change normalised by prior stock price ($S\Delta$ EPS), ABR_t is 1-month Fama-French three-factor model adjusted returns at the end of month t (current earnings announcement month), ABR_{t+1} 1-month Fama-French three-factor model adjusted returns at the end of month $t+1$, ABR_{t+2} 1-month Fama-French three-factor model adjusted returns at the end of month $t+2$, and Consistency is the length of sequences of annualised earnings-per-share changes scaled by prior stock price in the most current quarter. This sample is composed of all the companies that are in the S&P500 index from 1991 to 2006 (including those companies that were deleted during this sample period). There are a total of 525 companies yielding 23,017 company quarters of earnings-per-share changes in the final sample. Some 837 S&P500 constituent companies have quarterly changes data in my sample and my final sample companies derive from including only companies for which share-price performance including benchmark adjustments can be calculated.

Panel A: Descriptive statistics

Variable	No. of Obs.	Mean	Median	Std. Dev.	Min.	Max.	Skew.	Kurtosis
BHAR	23017	0.004	0.005	0.055	-0.512	0.511	-0.062	9.206
CAR	23017	0.032	0.029	0.223	-1.589	4.575	0.894	17.717
EPS	23017	1.006	0.88	5.99	-411.2	22.58	-58.456	3954.7
ΔEPS	23017	0.124	0.113	9.611	-372	534	0.187	20.45
$S\Delta$EPS	23017	0.006	0.004	0.186	-1	1	0.186	20.45
ABR_t	23017	0.004	0.002	0.107	-0.727	1.326	0.728	11.18
ABR_{t+1}	23017	0.015	0.008	0.123	-0.860	5.487	4.705	179.87
ABR_{t+2}	23017	0.009	0.007	0.107	-0.685	2.649	1.693	33.026
ABR_{t+3}	23017	0.004	0.002	0.107	-0.727	1.326	0.723	11.37
Consistency	23017	3.274	3	6.560	-12	12	-0.157	-2.021

Panel B: Correlation matrix (Spearman Correlations are shown above the diagonal with Pearson below)

	BHAR	CAR	EPS	ΔEPS	SΔEPS	ABR_{it}	ABR_{it+1}	ABR_{it+2}	ABR_{it+3}	Consistency
BHAR	1	0.992	-0.004	0.083	0.099	0.446	0.494	0.425	0.468	0.064
CAR	0.979	1	-0.029	0.078	0.094	0.434	0.500	0.426	0.468	0.052
EPS	0.068	0.050	1	0.222	0.118	0.029	-0.030	-0.012	0.017	-0.004
ΔEPS	0.005	0.003	0.001	1	0.948	0.057	0.037	0.029	0.049	0.622
SΔEPS	0.044	0.044	0.008	0.059	1	0.061	0.051	0.039	0.054	0.633
ABR_{it}	0.478	0.457	0.042	0.007	0.034	1	-0.047	-0.027	0.434	0.057
ABR_{it+1}	0.496	0.545	-0.001	0.011	0.020	-0.072	1	0.012	0.020	0.024
ABR_{it+2}	0.470	0.480	0.039	-0.014	0.006	-0.022	0.027	1	-0.012	0.007
ABR_{it+3}	0.521	0.519	0.025	0.001	0.029	0.053	0.033	-0.008	1	0.046
Consistency	0.057	0.040	0.052	0.014	0.256	0.044	0.012	-0.008	0.035	1

Table 4.4 continued

Panel C: Skewness of quarterly earnings-per-share changes by length and sign of earnings sequence

Panel C breaks up the distribution of EPS change sequences as each year of the quarterly run in EPS changes cumulates. I calculate the mean, median, kurtosis, standard deviation, and skewness of grouped sequence lengths of 1 to 4, 5 to 8, and 9 to 12 quarters of either consecutive EPS falls or rises (i.e. each successive year of consecutive falls and rises).

Sequence Length	Number of Obs.	Mean	Median	Skewness	Kurtosis	Std. Dev.
9 to 12 Consecutive falls	792	-7.780	-1.011	-27.933	783.959	2.06E+15
5 to 8 Consecutive falls	2369	-9.030	-0.567	-35.116	1250.447	3.13E+14
1 to 4 Consecutive falls	3566	-2.800	-0.384	-59.69	3564	1.67E+14
1 to 4 Consecutive rises	6716	-1.030	0.24	-81.932	6714	8.42E+14
5 to 8 Consecutive rises	3059	0.453	0.279	11.226	216.044	0.749
9 to 12 consecutive rises	6515	0.263	0.175	36.057	1519.854	0.82

Panel D: Skewness of three-month Buy-and-Hold Fama-French three-factor adjusted returns by length and sign of earnings sequence

Panel D breaks up the distribution of EPS change sequences as a year of the quarterly run in EPS changes cumulates. I calculate the mean, median, standard deviation, kurtosis, and skewness of three-month buy-and-hold Fama-French three-factor model adjusted returns matched with their respective grouped EPS sequence lengths for 1 to 4, 5 to 8, and 9 to 12 quarters of consecutive EPS falls or rises (i.e. each successive year if consecutive falls and rises).

Sequence Length	Number of Obs.	Mean	Median	Skewness	Kurtosis	Std. Dev.
9 to 12 consecutive falls	792	0.004	0.006	0.239	6.438	0.058
5 to 8 Consecutive falls	2369	-0.001	0.001	0.035	5.821	0.06
1 to 4 Consecutive falls	3566	-0.001	0.0004	0.077	9.177	0.061
1 to 4 Consecutive rises	6716	0.002	0.003	-0.194	9.622	0.058
5 to 8 Consecutive rises	3059	0.008	0.008	0.15	12.056	0.051
9 to 12 consecutive rises	6515	0.007	0.007	-0.024	8.229	0.046

Table 4.5

Panel A: Distribution of sequences of quarterly EPS rises and falls across the sample

This table presents the distribution of sequences of quarterly earnings-per-share changes across the sample companies. The distribution shows that quarterly earnings rises are far more common than quarterly earnings falls.

Consistency	Proportion	Std. Err.	[95% Conf. Interval]
-12	1.067%	0.0006753	0.0093464 - 0.0119936
-11	0.527%	0.0004759	0.0043374 - 0.006203
-10	0.756%	0.0005693	0.0064438 - 0.0086756
-9	1.097%	0.0006847	0.0096303 - 0.0123144
-8	1.395%	0.000771	0.012442 - 0.0154642
-7	0.397%	0.0004135	0.0031637 - 0.0047848
-6	4.661%	0.0013856	0.0438953 - 0.0493269
-5	3.845%	0.0012637	0.0359696 - 0.0409236
-4	4.303%	0.0013337	0.0404115 - 0.0456398
-3	5.309%	0.0014737	0.0502023 - 0.0559794
-2	5.918%	0.0015509	0.0561419 - 0.0622217
1	13.335%	0.0022344	0.1289739 - 0.1377331
2	5.957%	0.0015557	0.0565214 - 0.0626199
3	5.223%	0.0014623	0.0493606 - 0.0550931
4	4.700%	0.001391	0.0442733 - 0.0497264
5	4.083%	0.0013006	0.0382732 - 0.0433718
6	3.525%	0.0012121	0.0328742 - 0.0376257
7	3.028%	0.0011263	0.0280744 - 0.0324897
8	2.626%	0.0010511	0.0242044 - 0.0283249
9	2.385%	0.0010028	0.02188 - 0.025811
10	2.315%	0.0009885	0.0212168 - 0.0250919
11	2.065%	0.0009347	0.0188168 - 0.0224809
12	21.483%	0.0026994	0.2095347 - 0.2201167

Panel B: Shapiro-Wilk W test for normality

Variable	Obs	W	V	z	Prob>z
Consistency	23017	0.988	120.88	13.099	0.00

Table 4.6: Panel regression of sequence of quarterly EPS changes and monthly abnormal returns

The table below shows the intercept and the estimates of the panel regression model for monthly Fama-French three-factor model adjusted returns. The regression model is $ABR_{it} = \alpha + \beta_1 CONSIS + \beta_2 S\Delta EPS + \beta_3 CONSIS * S\Delta EPS + \epsilon_t$. where ABR_{it} is the 1-month Fama-French three-factor model adjusted returns at time t , $CON SIS$ (Consistency) is the length of quarterly earnings change sequence, 1, 2,,,,,,12 denoting EPS change sequences lasting 1 quarter, 2 consecutive quarters, 3 consecutive quarters, 12 consecutive quarters etc.; $S\Delta EPS$ is the change in annualised quarterly EPS (DeltaEPS) normalised by prior price, $CON SIS * S\Delta EPS$ is an interaction term measuring the interaction between Consistency and DeltaEPS, and ϵ_t random error. The sample includes all the S&P500 constituent stocks from January 1991 to December 2006. The t-statistics are reported in parenthesis and ***, **, * indicates statistical significance at a 1%, 5%, and 10% confidence level. The reported t values are subject to robust heteroskedasticity correction following White (1980).

Month	Intercept	Consistency	DeltaEPS	Consis*SΔEPS	N
ABR_{it}	0.200%** (2.12)	0.073%*** (6.36)			23013
	0.223%** (2.37)	0.064%*** (5.71)	1.260%** (2.15)		23013
	-0.001% (-0.20)	0.074%*** (6.64)	1.690%*** (2.92)	0.056%*** (5.65)	23013
ABR_{it+1}	1.410%*** (12.75)	0.019% (1.55)			23013
	1.440%*** (12.45)	0.009% (0.68)	1.303% (1.37)		23013
	1.060%*** (9.71)	0.030%** (2.19)	1.990%** (2.03)	0.930%*** (6.03)	23013
ABR_{it+2}	0.100%** (11.06)	-0.014% (-1.22)			23013
	1.005%** (11.32)	-0.00017 (-1.66)	0.547% (0.84)		23013
	0.712%** (7.50)	-0.00002 (-0.27)	1.080% (1.75)	0.720%*** (4.95)	23013

Table 4.7: Regression of three-month buy-and-hold Fama-French three-factor model adjusted returns and Consistency of quarterly EPS changes

This table shows the OLS regression of three-month buy-and-hold Fama-French three-factor model adjusted returns on Consistency (the sequences of annualised quarterly earnings-per-share changes). The regression model is $BHAR_{it} = \alpha + \beta_1 CONSIS + \beta_2 S\Delta EPS + \beta_3 CONSIS * S\Delta EPS + \epsilon_t$, where $BHAR_{it}$ is the three-month buy-and-hold Fama-French three-factor model adjusted returns at time t , $CONSIS$ (Consistency) is the length of the quarterly earnings change sequence, 1, 2, ..., 12 denoting earnings change sequences lasting 1 quarter, 2 consecutive quarters, 3 consecutive quarters, 12 consecutive quarters etc.; $S\Delta EPS$ is the change in annualised quarterly EPS (DeltaEPS) normalised by prior price, $CONSIS * S\Delta EPS$ is an interaction term measuring the interaction between Consistency and DeltaEPS, and ϵ_t random error. The sample includes all the S&P500 constituent stocks from January 1991 to December 2006. The t-statistics are reported in parenthesis and ***, **, * indicates statistical significance at a 1%, 5%, and 10% confidence level. The reported t values are subject to robust heteroskedasticity correction following White (1980).

	Intercept	DeltaEPS	Consistency	Consis*SΔEPS	N	R ²
BHAR_{it}						
	0.30%***(10.00)	0.005% (1.14)			23013	0.06
	0.20%***(4.78)	0.005%(0.68)	0.05%***(8.77)		23013	0.06
	0.20%***(5.03)	0.004%(0.28)	0.04%***(8.54)	-0.001% (-1.51)	23013	0.06

Table 4.8: Panel regression of buy-and-hold abnormal returns and different durations of sequences of quarterly EPS changes

Panels A, B, and C of this table shows the intercept and estimates of the panel regression of three-month buy-and-hold Fama-French three-factor adjusted returns on Consistency (sequence of quarterly EPS change). Panel D presents the OLS regression estimates of the same regression. The regression model is: $BHAR_{it} = \alpha + \beta_1 CONSIS + \beta_2 S\Delta EPS + \beta_3 DUMMY1 + \beta_4 DUMMY2 + \beta_5 DUMMY3 + \beta_6 YEAR + \epsilon_t$. where $BHAR_{it}$ is the 3-month buy-and-hold Fama-French three-factor model adjusted returns at time t , $CON SIS$ (Consistency) is the length of the quarterly earnings change sequence, 1, 2, , , , , , , 12 denoting earnings change sequences lasting 1 quarter, 2 consecutive quarters, 3 consecutive quarters, 12 consecutive quarters etc.; $S\Delta EPS$ is the change in annualised quarterly EPS (DeltaEPS) normalised by prior price; $DUMMY1$ represents either **Rise1, Rise2, Rise3, or Rise4** (**Rise1** captures the sequence of quarterly EPS rises and falls of more than eight quarters; **Rise2** captures the sequence of quarterly EPS rises and falls eight quarters or less; **Rise3** captures the sequences of quarterly EPS rises and falls of four quarters or less; **Rise4** captures the sequence of quarterly EPS rises and falls of two and three quarters), $DUMMY2$ represents either **More2yearneg, Less2yearneg** or **Less1yearneg**: (**More2yearneg** = is a dummy variable that equals 1 for consistent quarterly earnings fall sequences beyond eight quarters and zero otherwise; **Less2yearneg** = is a dummy variable that equals 1 for consistent quarterly earnings fall sequences of eight quarters or less and zero otherwise; **Less1yearneg** = is a dummy variable that equals 1 for consistent quarterly earnings fall sequences of four quarters or less and zero otherwise), $DUMMY3$ represents either **More2yearpos, Less2yearpos** or **Less1yearpos**: (**More2yearpos** = is a dummy variable that equals 1 for consistent quarterly earnings rise sequences beyond eight quarters and zero otherwise or **Less2yearpos** = is a dummy variable that equals 1 for consistent quarterly earnings rise sequences of eight quarters or less and zero otherwise or **Less1yearpos** = is a dummy variable that equals 1 for consistent quarterly earnings rise sequences of four quarters or less and zero otherwise), $YEAR$ is the year in my sample period from 1991 to 2006 in which the quarterly earnings sequence is recorded, and ϵ_t is random error. The sample includes all the S&P500 constituent stocks from January 1991 to December 2006. The t-statistics are reported in parenthesis and ***, **, * indicates statistical significance at a 1%, 5%, and 10% confidence level. For the OLS regression in panel D, the reported t values are subject to robust heteroskedasticity correction following White (1980).

Panel A: Consistent sequence of quarterly EPS changes for more than two years								
BHAR_{it}	Intercept	Year	Consistency	DeltaEPS	Rise1	More2yearneg	More2yearpos	N
	132%** (7.58)	-0.066%*** (-7.74)	0.092%*** (4.19)	0.900%*** (2.68)	-0.254% (-1.34)	1.161%*** (4.02)	-0.50%** (-2.43)	23017

Panel B: Consistent sequence of quarterly EPS changes for less or equal to eight quarters

BHAR_{it}							
Intercept	Year	Consistency	DeltaEPS	Rise2	Less2yearneg	Less2yearpos	N
133.1%***(7.64)	-0.066%***(-7.57)	0.092***(4.19)	0.900%***(2.68)	-1.910%***(3.47)	-1.200%***(-4.02)	0.500%***(2.68)	23017

Panel C: Consistent sequence of quarterly EPS changes for less or equal to four quarters

BHAR_{it}							
Intercept	Year	Consistency	DeltaEPS	Rise3	Less1yearneg	Less1yearpos	N
132.7%***(7.62)	-0.066%***(-7.61)	-0.011% (-0.56)	0.937%***(2.76)	0.748%***(2.14)	-0.14% (-0.80)	-0.56%***(-3.04)	23017

Panel D: Consistent sequence of quarterly EPS changes for two and three quarters (OLS regression estimates)

BHAR_{it}								
Intercept	Year	Consistency	DeltaEPS	Rise4	More2yearneg	More2yearpos	N	R²
135%*** (9.64)	-0.07%*** (-9.62)	0.09% (4.52)	0.04% (0.73)	0.748%*** (2.14)	1.00% (4.19)	-0.50%*** (-3.00)	23017	0.05

Table 4.9: Sub-period Analysis

This table reports the panel estimates of the price impact of consistent quarterly earnings patterns. Panel A shows the results for the first period from January 1991 to December 1998 and Panel B shows the results for the second period from January 1999 to December 2006. The regression model is: $BHAR_{it} = \alpha + \beta_{CONSIS} + \beta_1 \Delta EPS + \beta_2 DUMMY1 + \beta_3 DUMMY2 + \beta_4 DUMMY3 + \beta_5 YEAR + \epsilon_t$. where $BHAR_{it}$ is the 3-month buy-and-hold Fama-French three-factor model adjusted returns at time t , $CONSIS$ (Consistency) is the length of the quarterly earnings change sequence, 1, 2, ..., 12 denoting earnings change sequences lasting 1 quarter, 2 consecutive quarters, 3 consecutive quarters, 12 consecutive quarters etc.; ΔEPS (DeltaEPS) is the absolute change in annualised quarterly earnings-per-share normalised by prior price; $DUMMY1$ represents **Rise** which captures the consistent sequences of quarterly EPS rises and falls of more than eight quarters; $DUMMY2$ represents **More2yearneg** which equals 1 for a consistent sequence of quarterly EPS falls of more than eight quarters and zero otherwise; $DUMMY3$ represents **More2yearpos** which equals 1 for a consistent sequence of quarterly EPS rises of more than eight quarters and zero otherwise; $YEAR$ is the year in my sample period from 1991 to 2006 in which the quarterly earnings sequence is recorded, and ϵ_t is random error. The sample includes all the S&P500 constituent stocks from January 1991 to December 2006. The t-statistics are reported in parenthesis and ***, **, * indicates statistical significance at a 1%, 5%, and 10% confidence level.

Panel A: Panel regression of buy-and-hold abnormal returns with different durations of sequences of quarterly EPS changes (1991 - 1998)

	Intercept	Year	Consistency	DeltaEPS	Rise	More2yearneg	More2yearpos	N
$BHAR_{it}$	-75.510% (-1.37)	0.038% (1.39)	0.120%***(4.08)	0.877%** (2.10)	-0.679%** (-2.57)	1.267%*** (3.04)	-0.945%***(-3.47)	11149

Panel B: Panel regression of buy-and-hold abnormal returns with different durations of sequences of quarterly EPS changes (1999 - 2006)

	Intercept	Year	Consistency	DeltaEPS	Rise	More2yearneg	More2yearpos	N
$BHAR_{it}$	-194.560%*** (3.45)	0.097%*** (3.44)	0.035% (1.17)	0.704% (1.32)	0.234% (0.89)	0.882%** (2.30)	0.002% (0.01)	11868

Table 4.9 continued

This table reports the panel estimates of price impact of consistent quarterly earnings patterns on monthly abnormal returns. Panel C shows the results for the first period from January 1991 to December 1998 and Panel D shows the results for the second period from January 1999 to December 2006. The table below shows the intercept and the estimates of the panel regression model for 1-month Fama-French three-factor model adjusted returns. The regression model is $ABR_{it} = \alpha + \beta_{CONSIS} + \beta_1 S\Delta EPS + \beta_2 CONSIS * S\Delta EPS + \epsilon_t$, where ABR_{it} is the 1-month Fama-French three-factor model adjusted returns at time t , $CONSIS$ (Consistency) is the length of the quarterly earnings change sequence of 1, 2, ..., 11 to 12 denoting earnings change sequences lasting 1 quarter, 2 consecutive quarters, 3 consecutive quarters, 12 consecutive quarters etc.; $S\Delta EPS$ is the change in annualised quarterly EPS (DeltaEPS) normalised by prior price, $CONSIS * S\Delta EPS$ is an interaction term measuring the interaction between Consistency and DeltaEPS, and ϵ_t is random error. The sample includes all the S&P500 constituent stocks from January 1991 to December 2006. The t-statistics are reported in parenthesis and ***, **, * indicates statistical significance at a 1%, 5%, and 10% confidence level.

Panel C: Panel regression of sequence of quarterly EPS and 1-month Fama-French three-factor adjusted returns (1991 – 1998)

Month	Intercept	Consistency	DeltaEPS	Consis*SΔEPS	N
ABR_{it}	0.930%***(7.33)	0.032%** (2.24)			11147
	0.940%***(7.49)	0.027% (1.88)	0.780% (1.11)		11147
	0.706%***(5.86)	0.036%** (2.59)	0.962% (1.44)	0.465%***(3.90)	11147
ABR_{it+1}	1.890%***(12.13)	0.003% (0.19)			11148
	1.920%***(11.53)	-0.012% (-0.67)	1.870% (1.36)		11148
	1.360%***(9.59)	0.013% (0.75)	2.290% (1.66)	1.080%***(4.91)	11148
ABR_{it+2}	0.683%***(5.37)	0.025% (1.63)			11148
	0.696%***(5.63)	0.019% (1.42)	0.689% (0.73)		11148
	0.362%***(2.88)	0.033%** (2.48)	0.898% (1.04)	0.680%***(3.11)	11148

Panel D: Panel regression of sequence of quarterly EPS and 1-month Fama-French three-factor adjusted returns (1999 - 2006)

Month	Intercept	Consistency	DeltaEPS	Consis*SΔEPS	N
ABR_{it}	-0.387%***(-3.15)	0.092%***(5.56)			11866
	-0.350%***(-2.77)	0.079%***(4.68)	1.975% (1.88)		11866
	-0.556%***(-4.39)	0.094%***(5.51)	2.867%** (2.49)	0.647%*** (3.36)	11866
ABR_{it+1}	1.054%***(7.68)	0.016% (0.93)			11864
	1.056%***(7.61)	0.016% (0.87)	0.134% (0.13)		11864
	0.863%*** (5.94)	0.030% (1.62)	0.965% (0.87)	0.609%** (2.51)	11864
ABR_{it+2}	1.224%***(10.18)	-0.045%***(-2.69)			11864
	1.230%***(10.21)	-0.047%***(-2.86)	0.331% (0.42)		11864
	0.959%***(7.54)	-0.027% (-1.61)	1.507% (1.78)	0.857%*** (4.73)	11864

Table 4.10: Analysis of data by industry classification

This table reports the panel estimates of price impact of consistent quarterly earnings patterns. Panel A shows the results for the first period from January 1991 to December 1998 and Panel B shows the results for the second period from January 1999 to December 2006. The regression model is: $BHAR_{it} = \alpha + \beta_1 CONSIS + \beta_2 S\Delta EPS + \beta_3 DUMMY1 + \beta_4 DUMMY2 + \beta_5 DUMMY3 + \beta_6 YEAR + \epsilon_t$. where $BHAR_{it}$ is the 3-month buy-and-hold Fama-French three-factor model adjusted returns at time t , $CONSIS$ (Consistency) is the length of the quarterly earnings change sequence, 1, 2, ..., 12 denoting earnings change sequences lasting 1 quarter, 2 consecutive quarters, 3 consecutive quarters, 12 consecutive quarters etc.; $S\Delta EPS$ (DeltaEPS) is the absolute change in annualised quarterly earnings-per-share normalised by prior price; $DUMMY1$ represents either **Rise1**, **Rise2**, or **Rise3** (**Rise1** captures the sequence of quarterly EPS rises and falls of more than eight quarters; **Rise2** captures the sequence of quarterly EPS rises and falls of eight quarters or less; **Rise3** captures the sequences of quarterly EPS rises and falls of four quarters or less; $DUMMY2$ represents either **More2yearneg**, **Less2yearneg** or **Less1yearneg**: (**More2yearneg** = a dummy variable that equals 1 for consistent sequences of quarterly EPS falls of more than eight quarters and zero otherwise or **Less2yearneg** = a dummy variable that equals 1 for consistent sequences of quarterly EPS falls of eight quarters or less and zero otherwise or **Less1yearneg** = a dummy variable that equals 1 for consistent sequences of quarterly EPS falls of four quarters or less and zero otherwise), $DUMMY3$ represents either **More2yearpos**, **Less2yearpos** or **Less1yearpos**: (**More2yearpos** = a dummy variable that equals 1 for consistent sequences of quarterly EPS rises of more than eight quarters and zero otherwise or **Less2yearpos** = is a dummy variable that equals 1 for consistent sequences of quarterly EPS rises of eight quarters or less and zero otherwise or **Less1yearpos** = is a dummy variable that equals 1 for consistent sequences of quarterly EPS rises of four quarters or less and zero otherwise), $YEAR$ is the year in my sample period from 1991 to 2006 in which the sequence of quarterly EPS changes is recorded, and ϵ_t is random error. The sample includes all the S&P500 constituent stocks from January 1991 to December 2006. The t-statistics are reported in parenthesis and ***, **, * indicates statistical significance at a 1%, 5%, and 10% confidence level.

Panel A: Consistent sequence of quarterly EPS rises and falls for more than eight quarters

$BHAR_{it}$	Intercept	Year	Consistency	DeltaEPS	Consis* $S\Delta EPS$	Rise1	More2yearneg	More2yearpos	N
Sector									
Utilities	-12.406% (-0.25)	0.006% (0.36)	-0.072% (-1.37)	0.100% (0.06)	-0.173% (-0.30)	0.832% (1.89)	0.562% (0.69)	1.187% (1.71)	1257
Telecomm. services	533.030%*** (3.06)	-0.266%*** (-3.06)	0.114% (0.74)	-0.865% (-1.58)	1.106%*** (6.03)	-1.469% (-1.35)	1.675% (0.63)	0.296% (0.23)	309
Information tech.	236.407%*** (2.84)	-0.118%*** (-2.84)	0.097% (0.91)	1.856%*** (3.19)	0.521%*** (3.86)	0.308% (0.36)	0.069% (0.05)	-0.583% (-0.59)	2220
Financials	120%*** (3.98)	-0.060%*** (-3.97)	0.024% (0.63)	0.739% (1.07)	0.579%** (2.25)	0.305% (0.92)	0.570% (0.84)	-0.118% (-0.32)	2736
Health Care	-78.150% (-1.07)	0.039% (1.08)	0.131% (1.75)	-0.690% (-0.57)	0.651%** (2.26)	-0.292% (-0.48)	0.549% (0.26)	-1.290%** (-2.06)	1617
Consumer Staples	93.950%*** (2.93)	-0.047%*** (-2.93)	0.097% (1.88)	0.300% (0.52)	1.252%*** (6.60)	-0.029% (-0.05)	0.712% (0.58)	-0.610% (-1.44)	1658
Consumer Discretionary	93.280% (1.78)	-0.046% (-1.79)	0.075% (1.00)	0.004% (0.00)	1.130%*** (4.81)	0.259% (0.36)	0.522% (0.51)	-0.595% (-0.95)	2759
Industrials	87.210%** (2.59)	-0.043%** (-2.58)	0.093% (1.82)	0.570% (0.76)	0.557% (1.82)	-0.529% (-1.12)	1.174% (1.93)	-0.529% (-1.12)	1777
Materials	96.540% (1.71)	-0.048% (-1.71)	0.065% (0.98)	4.030%** (2.40)	0.421% (1.73)	-0.030% (-0.05)	0.371% (0.56)	-0.375% (-0.54)	1100
Energy	-209.430%*** (-3.15)	0.105%*** (3.15)	-0.008% (-0.10)	0.409% (0.48)	0.600%*** (3.11)	0.194% (0.29)	-0.659% (-0.88)	-0.923% (-0.88)	1149

Table 4.10 continued

Panel B: Consistent sequence of quarterly EPS rises and falls for less or equal to eight quarters									
BHAR _{it}	Intercept	Year	Consistency	DeltaEPS	Consis*SΔEPS	Rise2	Less2yearneg	Less2yearpos	N
Sector									
Utilities	-11.840% (-0.36)	0.006% (0.36)	-0.072% (-1.37)	0.100% (0.06)	-0.173% (-0.30)	1.457% (0.96)	-0.562% (-0.69)	-1.187% (-1.71)	1257
Telecomm. services	534.710%*** (3.04)	-0.266%*** (-3.06)	0.114% (0.74)	-0.865% (-1.58)	0.060%*** (6.03)	-2.849% (-0.73)	-1.675% (-0.63)	-0.296% (-0.23)	309
Information tech.	236.470%*** (2.82)	-0.118%*** (-2.84)	0.097% (0.91)	1.850%*** (3.19)	0.521%*** (3.86)	-0.345% (-0.13)	-0.069% (-0.05)	0.583% (0.59)	2220
Financials	120.630%*** (3.99)	-0.060%*** (-3.97)	0.024% (0.63)	0.739% (1.07)	0.579%** (2.25)	-0.384% (-0.36)	-0.570% (-0.84)	0.118% (0.32)	2736
Health Care	-77.560% (-1.17)	0.039% (1.20)	0.131% (1.71)	-0.690% (-0.84)	0.651%*** (3.56)	-2.133% (-1.08)	-0.550% (-0.48)	1.290% (1.86)	1617
Consumer Staples	94.660%*** (2.94)	-0.047%*** (-2.93)	0.097% (1.88)	0.300% (0.52)	1.250%*** (6.60)	-1.352% (-0.89)	-0.712% (-0.58)	0.610% (1.44)	1658
Consumer Discretionary	93.800% (1.79)	-0.046% (-1.79)	0.075% (1.00)	0.004% (0.00)	1.132%*** (4.81)	-0.859% (-0.48)	-0.522% (-0.51)	0.595% (0.95)	2759
Industrials	88.38%** (2.62)	-0.043%** (-2.58)	0.093% (1.82)	0.570% (0.76)	0.557%*** (2.76)	-2.049% (-1.86)	-1.174% (-1.93)	-1.704%** (-2.07)	1777
Materials	96.916% (1.72)	-0.048% (-1.71)	0.065% (0.98)	4.028%** (2.40)	0.421% (1.73)	-0.777% (-0.48)	-0.371% (-0.56)	0.375% (0.54)	1100
Energy	-210%*** (-3.15)	0.105%*** (3.15)	-0.008% (-0.10)	0.408% (0.48)	0.660%*** (3.11)	-0.069% (-0.04)	0.659% (0.88)	0.923% (0.88)	1149

Table 4.10 continued

Panel C: Consistent sequence of quarterly EPS rises and falls for less or equal to four quarters

BHAR _{it}	Intercept	Year	Consistency	DeltaEPS	Consis* Δ EPS	Rise3	Less1yearneg	Less1yearpos	N
Sector									
Utilities	-15.368% (-0.46)	0.008% (0.48)	0.048% (0.53)	0.228% (0.13)	-0.212% (-0.36)	-0.729% (-0.51)	-1.085% (-1.81)	0.057% (0.09)	1257
Telecomm. Services	524.720%*** (3.12)	-0.262%*** (-3.12)	-0.009% (-0.10)	-0.561% (-1.22)	1.154%*** (6.28)	0.374% (0.25)	-0.488% (-0.65)	-1.900% (-1.38)	309
Information tech.	226.090%** (2.65)	-0.113%** (-2.65)	0.078% (0.81)	1.825%*** (3.23)	0.55%*** (3.97)	0.346% (0.21)	0.422% (0.57)	0.479% (0.52)	2220
Financials	122.780%*** (4.10)	-0.061%*** (-4.10)	-0.012% (-0.34)	0.823% (1.12)	0.563%** (2.34)	0.467% (0.81)	-0.439% (-1.23)	-0.304% (-0.96)	2736
Health Care	-75.905% (-1.10)	0.037% (1.09)	-0.075% (-1.03)	-0.504% (-0.42)	0.615%** (2.07)	1.959% (1.47)	0.310% (0.58)	-0.894% (-1.11)	1617
Consumer Staples	89.370%*** (2.79)	-0.045%*** (-2.82)	0.002% (0.05)	0.305% (0.56)	1.299%*** (6.67)	1.338% (1.59)	0.752% (1.26)	-0.290% (-0.54)	1658
Consumer Discretionary	87.204% (1.67)	-0.044% (-1.69)	-0.041% (-0.65)	-0.032% (-0.03)	1.179%*** (5.10)	2.081% (1.93)	1.018%** (2.00)	-0.491% (-0.80)	2759
Industrials	88.747%** (2.59)	-0.044%** (-2.58)	0.030% (1.11)	0.723% (0.98)	0.591%*** (2.77)	-0.127% (-0.38)	-0.135% (-0.39)	-0.480% (-1.82)	1777
Materials	109.547%** (2.03)	-0.055%** (-2.04)	0.012% (0.20)	3.923%** (2.35)	0.464% (1.81)	0.688% (0.57)	0.711% (1.03)	0.041% (0.07)	1100
Energy	-208.110%*** (-2.82)	0.104%*** (2.82)	-0.189% (-1.66)	0.732% (0.78)	0.517%** (2.61)	2.533% (1.27)	-0.124% (-0.15)	-1.562% (-1.60)	1149

Table 4.11: Main regression model including dummy for ‘information discreteness’ (i.e. the company’s *IDz* value being above or below the sample *IDz* median value)

This table shows the OLS regression of three-month buy-and-hold Fama-French three-factor model adjusted returns on Consistency (the sequences of annualised quarterly earnings-per-share changes). The regression model is $BHAR_{it} = \alpha + \beta_1 CONSIS + \beta_2 S\Delta EPS + \beta_3 CONSIS * S\Delta EPS + \beta_4 IDz + \epsilon_t$. where $BHAR_{it}$ is the 3-month buy-and-hold Fama-French three-factor model adjusted returns at time t , $CONSIS$ (Consistency) is the length of the quarterly earnings change sequence of 1, 2,,,,,,, 11, and 12 denoting earnings change sequences lasting 1 quarter, 2 consecutive quarters, 3 consecutive quarters, 11 consecutive quarters, 12 consecutive quarters etc.; $S\Delta EPS$ is the change in annualised quarterly EPS (DeltaEPS) normalised by prior price, $CONSIS * S\Delta EPS$ is an interaction term measuring the interaction between Consistency and DeltaEPS, IDz is a dummy variable which takes the value of one when information discreteness as measured by equation 4.5 is above its median value and takes zero otherwise, and ϵ_t is random error. The IDz dummy captures the speed with which value relevant information enters price. The sample includes all the S&P500 constituent stocks from January 1991 to December 2006. The t-statistics are reported in parenthesis and ***, **, * indicates statistical significance at a 1%, 5%, and 10% confidence level. The reported t values are subject to robust heteroskedasticity correction following White (1980).

	Intercept	DeltaEPS	Consistency	Consis*SΔEPS	ID_z	N	R²
BHAR_{it}	-0.828%***(-2.81)	3.940%***(3.25)	0.090%***(2.86)	1.380%***(5.61)	1.046%***(2.66)	23017	0.13

Table 4.12: Bayesian estimates of the main regression model

The table presents the Bayesian estimates of the main regression in table 4.7. The regression model is $BHAR_{it} = \alpha + \beta_1 CONSIS + \beta_2 S\Delta EPS + \beta_3 CONSIS * S\Delta EPS + \epsilon_t$, where $BHAR_{it}$ is the 3-month buy-and-hold Fama-French three-factor model adjusted returns at time t , $CON SIS$ (Consistency) is the length of the quarterly earnings change sequence, 1, 2,,,,,,12 denoting earnings change sequences lasting 1 quarter, 2 consecutive quarters, 3 consecutive quarters, 12 consecutive quarters etc.; $S\Delta EPS$ is the change in annualised quarterly EPS (DeltaEPS) normalised by prior price, $CON SIS * S\Delta EPS$ is an interaction term measuring the interaction between Consistency and DeltaEPS, and ϵ_t random error. The sample includes all the S&P500 constituent stocks from January 1991 to December 2006. The Bayesian estimates show a weighted average of the investor's prior distribution of the parameters and their sample means. The weights of the sample mean increase as the estimation sample grows. Initially, the weight placed on the various variables (Consistency, DeltaEPS, and **Consis*SΔEPS**) is set to zero, and this action is consistent with due scepticism about the ability of fundamentals to explain abnormal returns. The estimates of regression coefficients are taken at the 5%, 50%, and 95% points of distribution of the three-month buy-and-hold Fama-French three-factor model adjusted returns.

Confidence Interval	Intercept	DeltaEPS	Consistency	Consis*SΔEPS
5%	-0.153%	1.137%	0.054%	0.442%
50%	-0.010%	1.786%	0.073%	0.569%
95%	0.133%	2.426%	0.092%	0.699%

Figure 4.1: The distribution of a Bayesian and a quasi-Bayesian (Freddy) posterior prior of earnings

Figure 4.1 below shows the distribution of expectations of a quasi-Bayesian investor (Freddy) as opposed to that of a Bayesian investor. For a Bayesian with a posterior probability of $1/6$ for earnings rises immediately following a fall in quarterly earnings, $1/3$ for a company recording no earnings change last quarter, and finally, $1/2$ for consecutive quarterly rises, there is an analogous distribution of zero, $1/3$, and $2/3$ for the quasi-Bayesian (Freddy) investor. Therefore the overall impact of a belief in the law of small numbers is to shift the distribution of inferred posterior probabilities of earnings rightwards. This figure graphically represents this rightward shift in posterior probabilities.

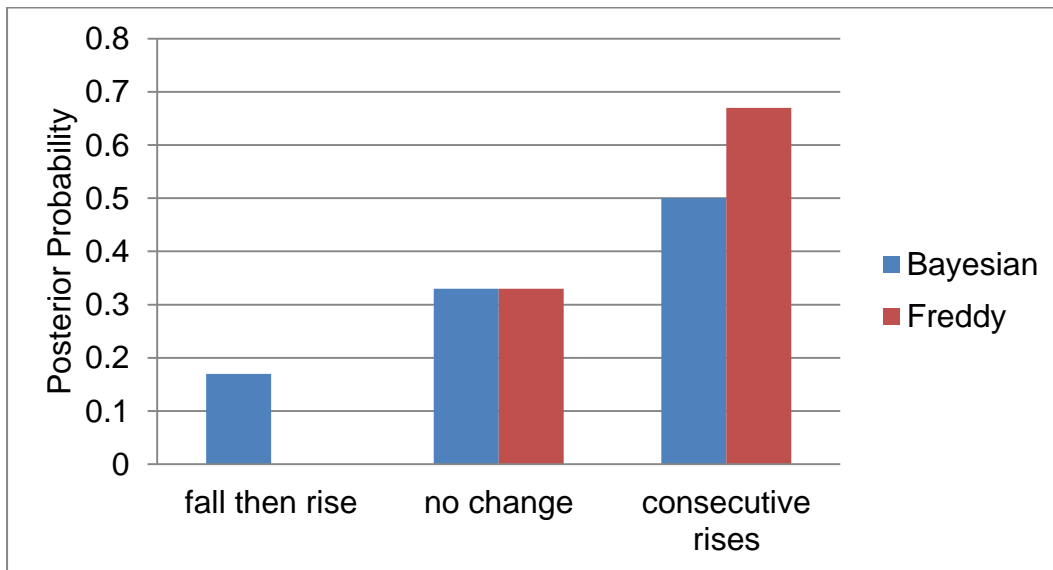


Figure 4.2: The distribution of sequences of quarterly EPS rises and falls traced over 12 quarters of data

Figure 4.2 provides the histogram of the percentage frequency distribution of sequences of quarterly EPS change in my sample. The figure shows that the asymmetric and uneven distribution of quarterly earnings-per-share changes in my sample date is striking. About 22% of the sample data derives from companies reporting quarterly earnings increases for at least three years or twelve quarters or more.

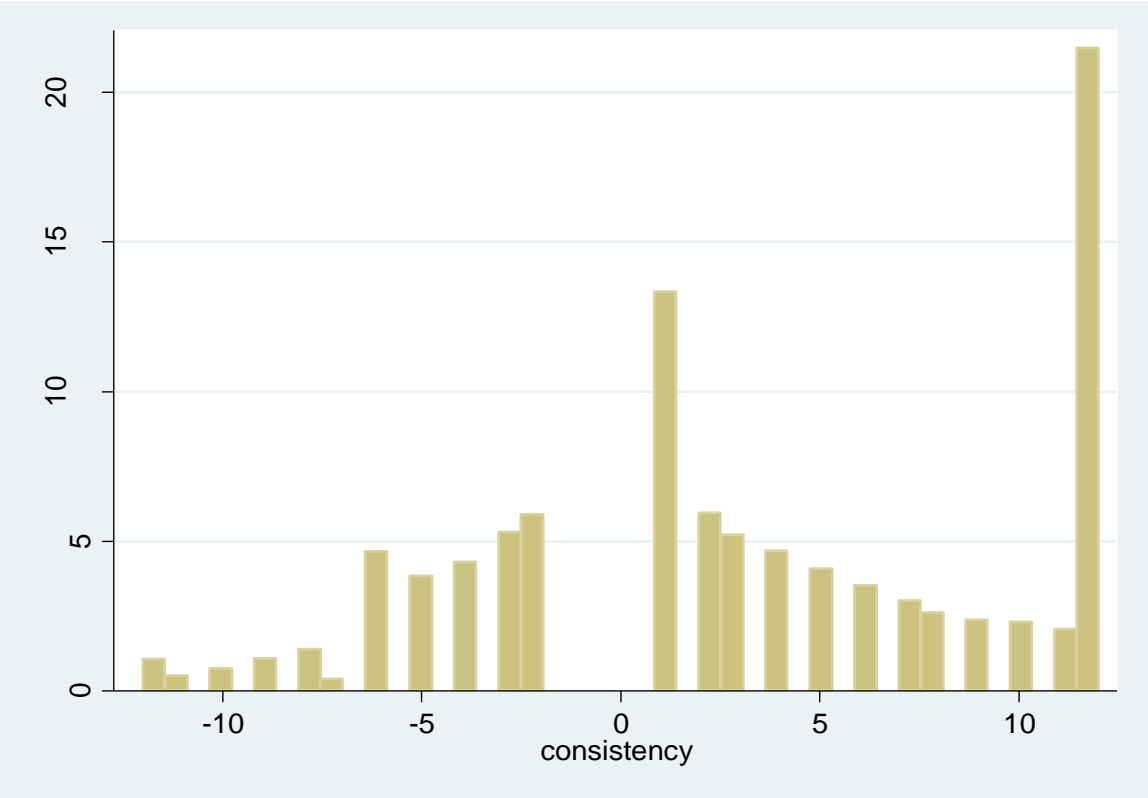


Figure 4.3: The distribution of annualised quarterly EPS changes normalised by prior year end stock price

Figure 4.3 shows the histogram of the percentage frequency distribution of raw annualised quarterly earnings changes normalised by prior price in the most recent quarter in my sample data. The distribution between quarterly earnings falls and rises is asymmetric and uneven. Quarterly earnings rises are much more common than quarterly earnings falls. The majority of my S&P500 companies seem to post incremental positive earnings quarter on quarter; about 62% of the quarterly earnings changes are very small in value and close to the zero point. This may be suggestive of some form of earnings management engaged in by managers to meet and beat targets, and this is well documented in the literature.

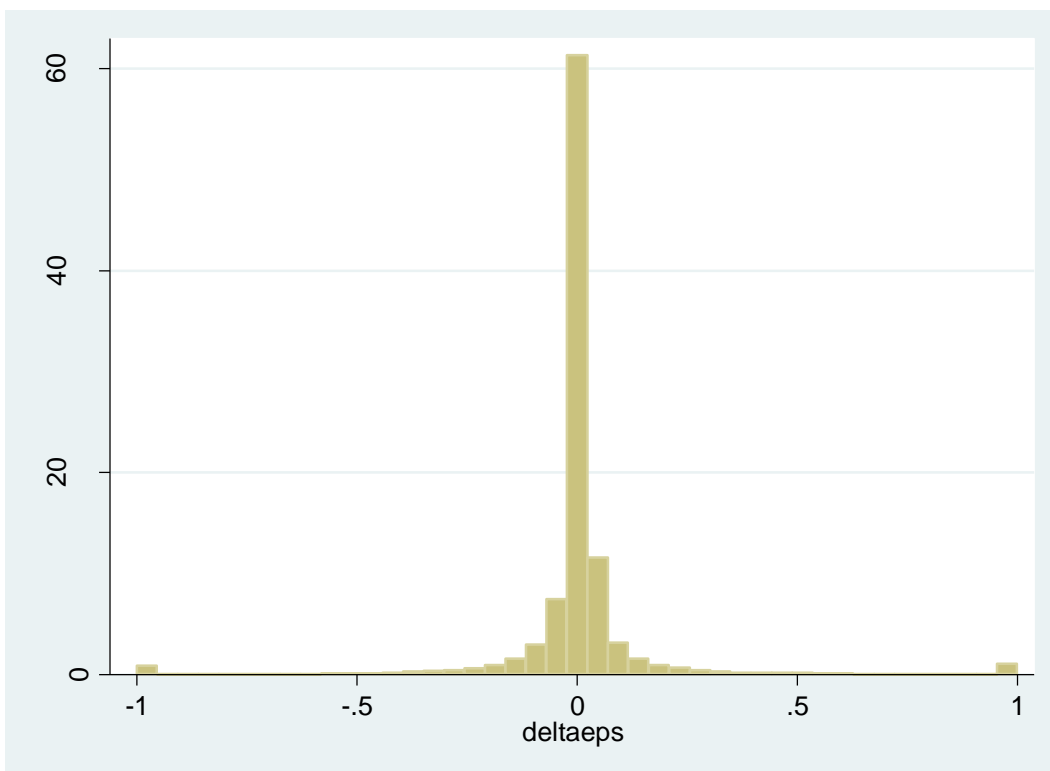


Figure 4.4: Mean EPS change by length of quarterly EPS rises and falls traced over 12 quarters of data

Figure 4.4 plots the means of annualised quarterly EPS changes over twelve quarters of consistent earnings rises and falls. The cumulatively larger nature of the repeated falls in quarterly EPS is very clear in the data while the scale of repeated quarterly earnings rises stabilises to smallish values for four quarters. Consistent quarterly declines in earnings seem to cumulate in fairly stable, possibly even manageable forms of corporate reporting in my sample data.

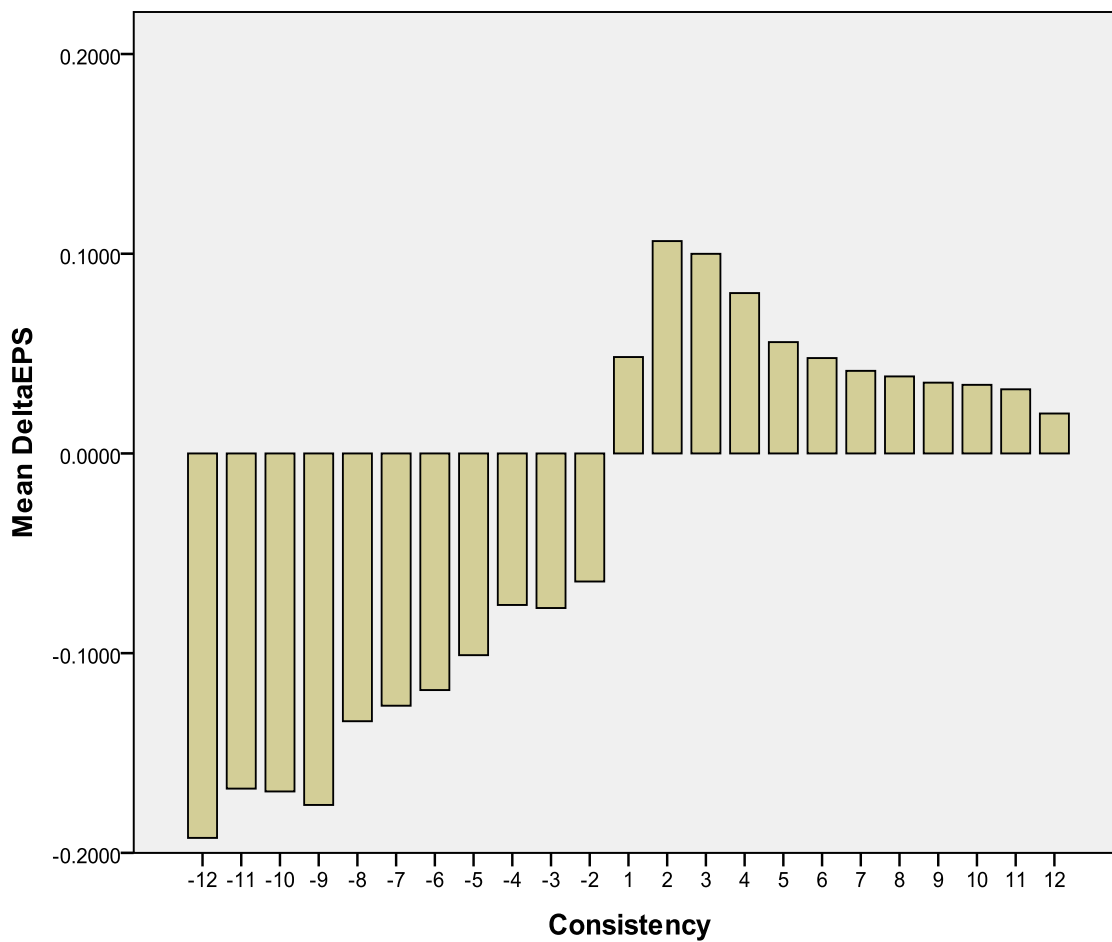


Figure 4.5: Mean three-month buy-and-hold Fama-French three-factor adjusted returns by Consistency

Figure 4.5 shows the relation between the three-month buy-and-hold Fama-French three-factor model adjusted returns and the quarterly earnings change sequences of increasing length, across losses/gains over three years' duration.

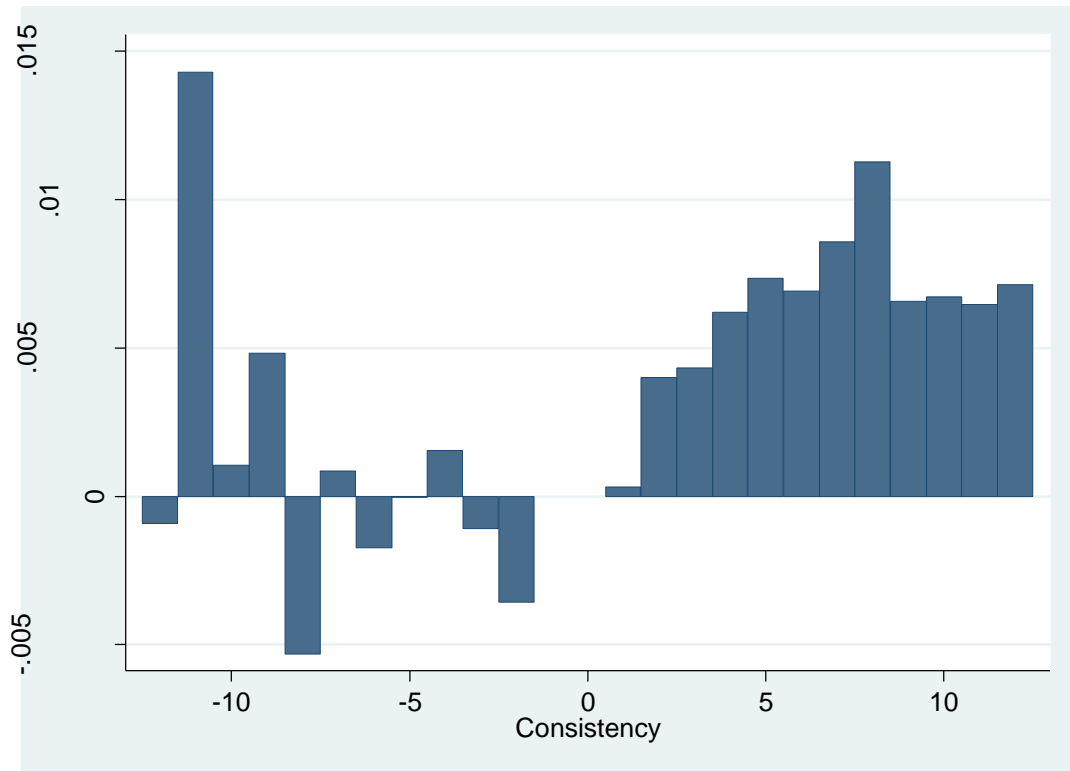
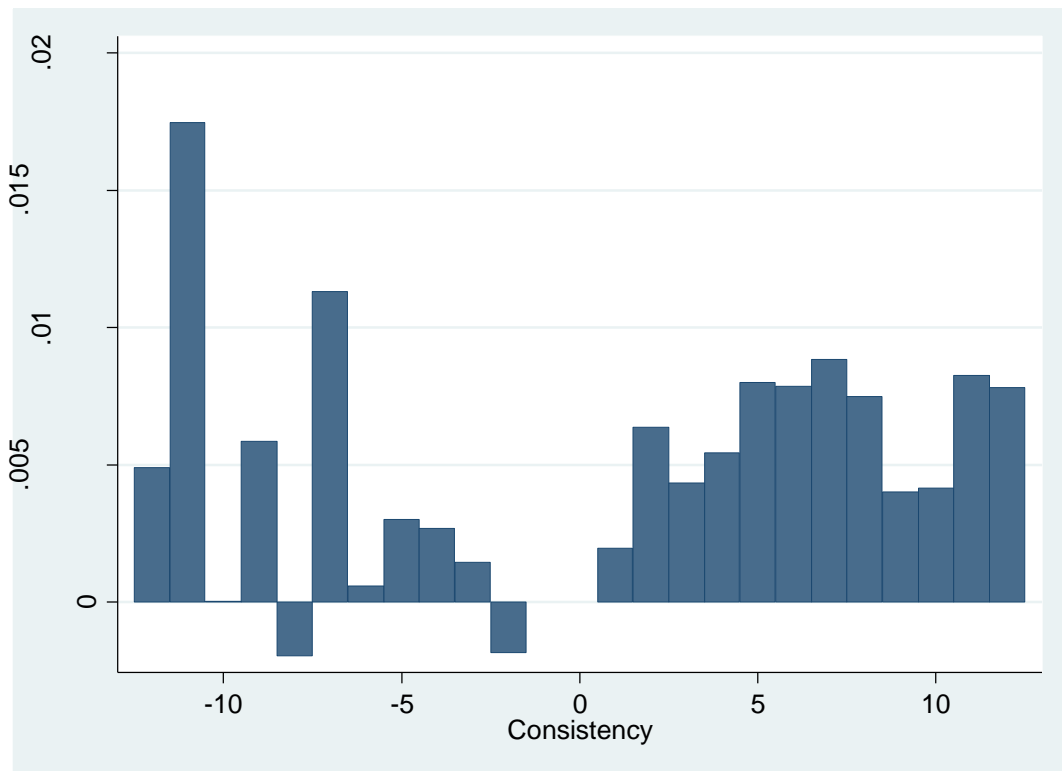


Figure 4.6: Median three-month buy-and-hold Fama-French three-factor adjusted returns by Consistency

Figure 4.6 simply reconstructs figure 4.5 using the median of the three-month buy-and-hold Fama-French three-factor model adjusted returns rather than the mean of the three-month buy-and-hold Fama-French three-factor model adjusted returns. The basic pattern of figure 4.4 showing cumulative quarterly earnings falls becoming more dramatic in scale while cumulative quarterly earnings growth stabilise to small values is confirmed by figures 4.5 and 4.6. This suggests that the pattern does not result from a few rogue, outlier observations which imply no broader trend in the data.



Chapter 5

Post-earnings announcement drift, streaks of earnings surprises, information uncertainty, and the gambler's fallacy

5.1 Introduction

In chapter 4, I introduced two theoretical models of earnings momentum (Barberis *et al* (1998), and Rabin (2002b)). I use the propositions of the models to show how sequences (streaks) of quarterly EPS rises and falls impact on stock returns³⁴. In chapter 4, the quarterly EPS change metric used was measured in a way that captures the market impact of sequences of quarterly EPS through to the next year's quarterly earnings announcement. The objective was to determine this impact and the subsequent earnings momentum in price within a medium-term window (three months). In this chapter, the fundamental hypotheses of the impact of sequences (streaks) of EPS changes on price in chapter 4, based mainly on Rabin (2002b), are extended further. Here, the focus is on testing the impact of streaks of earnings surprises (EPS rises and falls) on the S&P500 constituent companies' stock returns in a shorter window around the quarterly EPS announcement date. In order to ensure that the price response to sequences of EPS changes is not limited to the earnings momentum metric in chapter 4, a variant metric of earnings momentum is introduced in this chapter. This metric captures the change in the representative investor's expectation at earnings announcement in a different way. Here I calculate the change in a representative investor's expectation (earnings surprise) of quarterly earnings by taking the difference between the actual quarterly earnings and monthly analyst forecast of quarterly earnings in the most current quarter normalised by the prior year end price. This metric allows the investor's market expectations of earnings to reflect developments since the previous quarterly earnings announcement. I also test for how the interaction effect between streaks of earnings surprises and different information uncertainty proxies impacts on the stock market returns. The information uncertainty proxies and tests follow procedures in Zhang (2006a).

There is a need to understand earnings momentum better, given the strong evidence that stock markets underreact to recent earnings news. Subsequently, investors are prone to overinfer from dramatic price movements resulting from underreaction to earnings news, and this leads them to make incorrect forecasts. Again, in this chapter, I employ the propositions of Rabin's (2002b) model, as its predictions fit best with my data sample, as seen in the results of chapter 4. In addition, in this chapter, I examine further to see if the results of the model's predictions in chapter 4 remain consistent when the earnings surprise metrics and the impact period tested are changed.

³⁴ Note: 'streaks' in this chapter and 'sequences' in chapter 4 are used interchangeably.

The important alteration made in this chapter is that the change in investors' expectations (earnings surprise) for quarterly EPS outcomes is calculated using analysts' consensus forecasts of EPS and the actual EPS, as reported by the I/B/E/S database. This metric of change in investors' expectation is different from the metric used in chapter 4, which is based on the time series of reported actual quarterly earnings-per-share. This position on earnings momentum metrics has support in the finance literature. One such study is Livnat and Mendenhall (2006), who report that using two different earnings surprise metrics, one from analysts' forecast of earnings and actual quarterly EPS from the I/B/E/S database and another from a time series model, they observe that patterns of returns around future earnings announcements are different when generated by the alternative metrics of investors' earnings expectations. The authors conclude that the reason for this could be the fact that the two earnings surprise metrics are capturing different kinds of information about future quarterly EPS. So it will be interesting to see whether the two different metrics of earnings momentum and their streaks are able to capture earnings momentum in price according to Rabin's (2002b) propositions. In this chapter, I introduce information uncertainty proxies as control variables. In addition, I use information uncertainty proxies and streaks of earnings surprises to create interaction variables. The choice of control variables is made against the backdrop of the fact that high or low information uncertainty about a firm's quarterly EPS could impact upon returns around quarterly EPS announcement dates. I hypothesise that firms with high information uncertainty will exhibit larger earnings momentum on their returns around quarterly EPS announcement dates. This is because for this sub-sample of corporations, the earnings announcement resolves more uncertainty at that point in time than it does for low information uncertainty firms.

Furthermore, in this chapter, the main hypothesis remains the overinference bias which shows how investors observing sequences (streaks) of EPS rises and falls may interpret a firm's value incorrectly. How this behaviour consequently impacts on stock prices also remains fundamental in this chapter. In addition, I examine other hypotheses which include the impact of streaks of earnings surprises on stock price in the presence of different levels of uncertainty about the fundamental value of firms. For firms that consistently report quarterly EPS rises over long periods of time, one would expect the market to get used to their 'earnings news' and not be surprised when new confirming EPS outcomes are announced. In other words, the market's reaction to the earnings announcements of such firms (if anything) is expected to be weak and muted. To examine this behaviour, this chapter examines the impact that the information content of quarterly EPS has on price in the short window of three days – a time when the most recent earnings news hits the market. It is important to see how the market responds to the sudden change in investors'

expectations once the most recent EPS is announced. The chapter also seeks to show whether the post-earnings announcement drift is a result of investors' overinference from the information content of EPS with the arrival of earnings news. Additionally, the chapter seeks to understand whether subsequent market corrections following period of earnings momentum imply that investors have learnt the true nature of earnings news with the passage of time. Finally, it examines the valuation implications of information uncertainty around earnings announcements. It is well known that information uncertainty reduces the degree of anticipation of announced earnings and at the same time intensifies the response to earnings at the announcement date when uncertainty is partially or fully resolved.

I include information uncertainty proxies as control variables because S&P500 constituent firms are large capitalised as well as very liquid firms, with all of the main analysts following them, so I expect any earnings momentum effect caused by sequences (streaks) of earnings rises and falls to be wiped away (or at least reduced substantially) by information uncertainties surrounding their fundamentals over time. This is more so because, as has been argued in the literature at various times, the test window employed here is very short. Analysts tend to follow those firms that investors wish to invest in more than the less popular firms. In other words, analysts tend to cover those firms that are consistently doing well or at least reporting good earnings outcomes; they do not usually cover firms that consistently produce poor results. Consequently, this means that investors and all market participants have more information on the firms that analysts follow, therefore there is less uncertainty about those firms' fundamentals, and their stock price behaviour is less dramatic around quarterly earnings announcements and ameliorates any underreaction. So it is expected that firms with large analyst followings will be low information uncertainty firms.

In a nutshell, the main objectives of this chapter are threefold. First, I calculate buy-and-hold Fama-French three-factor adjusted post-earnings announcement returns in a shorter window of three days. This is in contrast to three months window applied in the chapter 4. The intention here is to examine the earnings momentum effect in a window that is as short as possible in order to eliminate contamination from sources other than the earnings announcement. Second, the earnings surprise metric used here is calculated using the consensus analysts' forecast of quarterly EPS and actual quarterly EPS from the I/B/E/S database. Some authors argue that the consensus analysts' forecast is a far better and more reliable measure of investors' expectation of quarterly EPS than the time series of actual EPS³⁵. This is because analysts adjust their forecast more often, usually on a monthly basis, thus continually incorporating new information into their forecasts. Furthermore, richer

³⁵ See Givoly and Lakonishok (1980, 1984), Livnat and Mendenhall (2006).

information sets from sources other than simple past EPS outcomes enter the forecast of next quarter's earnings. Analysts incorporate such factors as technological and regulatory shifts in a company's environment into their monthly forecasts. Third, six information uncertainty proxies are introduced as control variables for earnings momentum that is not associated with the most recent earnings shock. Through these three paths, I hope to show the robustness of my central argument in chapter 4 to various competing stories that might challenge its integrity.

5.2 Related literature and hypothesis development

Here I narrow down my literature review to those papers that are directly related to the hypotheses tested in this chapter. The section is obviously an extension of the broader literature review in chapter 2. The hypotheses tested in this chapter are derived following this literature review.

5.2.1 Experimental evidence of responses to lengthening streaks of EPS rises and falls

Each of the competing models of investors' underreaction/overreaction I reviewed in chapter 2 offers compelling stories on how information about earnings changes might be assimilated into price. However, the models provide us with no idea as to whether investors really think like that in practice. Bloomfield and Hales (2002) provide evidence from laboratory experiments to show that when asked to predict the outcome of a random draw, most peoples' forecasts are grounded in their observation of past reversions and continuations in the series. If they can see that the series have been subject to many reversals, they generally underreact to the most recent change, but if they observe an unbroken set of recent rises, or falls, they usually overreact to the most recent change. This is consistent with investors regarding repeated signals about the value as separating companies into 'star' and 'dog' categories. It is surprising that experimental subjects still behave in this manner even when they are told in advance that the series they observe is generated from a random process, that is, even when it is clear that inference based on past innovations in the series is irrational.

Asparouhova, Hertz, and Lemmon (2009) present a simple explanation of why the subjects in the Bloomfield and Hales (2002) experiments use past realisations of the process they observe to predict future outcomes. The authors argue that this is because the realisations that the subjects are presented with seem so unlikely to have been generated by a random process. Thus, even when they are told that they are predicting a random process, they do not believe they actually are. In correcting for this failure, they re-ran the Bloomfield and

Hales (2002) experiments, presenting subjects with eight past realisations of a random series that actually looks pretty random and asking them to predict the next outcome. When this is done, a pattern of biases far more consistent with Rabin's (2002b) framework emerges. While initially subjects regard immediate past changes as a trend likely to reverse swiftly, however, if that trend continues, they came to regard it as indicative of the underlying value of the asset. So investors cycle between initial enchantment by the gambler's fallacy (which for longer streaks presages the belief that changes they had regarded as transitory are, in fact, part of a broader trend of increasing/decreasing performance) and anticipation of reversal.

5.2.2 Streaks of quarterly earnings surprises and investor returns

A number of papers chronicle investor response to lengthening streaks of quarterly earnings rises and falls without attempting to invoke or confirm any broader theorisation of this empirical regularity. Thus, these papers try to infer a stock market response to earnings 'streakiness' (a propensity to streaks in quarterly earning changes) regardless of its origin or rationale. Barth, Elliot and Finn (1999) document that corporations reporting streaks of quarterly earnings surprises of five years or more exhibit higher stock returns, and these returns are not explained by either greater expected earnings growth or by standard risk proxies. The authors show that companies reporting long streaks of quarterly earnings rises enjoy significantly higher earnings multiples in their price, while those that report a falling trend suffer significantly worse multiples of earnings for their price. This finding further weakens the market efficiency argument that public information is instantaneously assimilated into price.

Frieder (2008) presents evidence concerning the type of trader that might be fuelling the emergence of momentum/underreaction regimes in prices. The author reports that at earnings announcement, as a streak of quarterly EPS rises lengthens, increasingly, a cohort of small trades typically associated with individual (possibly naïve) investors emerges in the market. The quarterly-earnings-change-chasing behaviour of investors executing small trades is costly for them, because the strategy yields significantly negative return. The persistence of momentum here may thus require that, as the saying goes "there is a noise trader born every minute" as successive generations of small traders get burned by larger and more sophisticated, larger trade, 'smart-money' traders. Frieder examines net order imbalances; this is the number of shares purchased compared to those sold by those trading small amounts of stocks and any response that may come from earnings surprises. If a series of quarterly earnings surprises is uncorrelated, as one would expect in an efficient market, they (streaks of earnings surprises) cannot influence order imbalances. However,

consistent with the predictions of the BSV model, Frieder finds that small traders make strongly significant net purchases just after streaks of positive earnings surprises commence, as compared to when a previous quarterly change is negative. Hence, investors tend to overextrapolate streaks of earnings performance when they observe consecutive EPS rises. In a more recent paper, Shanthikumar (2012) provides evidence showing similar trading patterns by small and large traders around earnings announcements. This study finds the relative intensity of small traders' trading grows as the length of streaks of positive EPS change grow. It appears that investors who trade small volumes, are individual, and thus possibly naïve, investors who exhibit a strong preference for buying into stocks with lengthening streaks of good earnings performance. This form of 'me too' investment by smaller trade size investors seems a strong candidate to explain the observed earning momentum present in mature markets.

5.2.3 Streaks of quarterly earnings surprises and the gambler's fallacy

There is a huge body of literature within market-based accounting research which discusses the scale and offers explanations for the existence of PEAD in stock returns. However a far smaller literature focuses on the market impact of streaks in quarterly EPS changes. Only a small number of researchers have specifically investigated the investor behaviour that the Rabin (2002b) model proposes. One of such papers is the Loh and Warachka (2012). The paper focuses on the stock market effect of lengthening streaks of earnings changes.

Loh and Warachka (2012) examine the propositions of Rabin's (2002b) model, which suggests that the gambler's fallacy causes investors to underreact to streaks of earnings surprises. The authors find that streaks of earnings surprises explain about 54% of PEAD returns. The authors also find that earnings surprise reversals have no explanatory power in explaining PEAD. They find that a trading strategy which buys stocks with positive streaks of earnings surprises and sells stocks with negative streaks of earnings surprises yields a statistically significant four-factor adjusted return. In order to uncover such a profile in the stock market response to earnings surprises around earnings announcements, Loh and Warachka (2012) undertake two types of trading rule tests. In their first set of tests, portfolios are formed simply on the basis of the 'streakiness' of the company's run of quarterly earnings announcements. Investors buy portfolios of companies that report confirming positive earnings surprises at the most recent earnings announcement, while they sell portfolios of stocks that reversed their lengthening streaks of positive earnings surprises in the most recent quarter earnings announcement. The authors report that this single-sort trading strategy yields a consistent average profit, even after reasonable controls for possible risk differences are made. It would appear that investors do indeed exhibit the

gambler's fallacy / law of small numbers effect that Rabin's (2002b) model envisages. The investors' susceptibility to the gambler's fallacy allows them to regard current earnings surprises as merely transitory, this behaviour being consistent with the gambler's belief that 'my luck must change'. This belief triggers earnings momentum in prices that underpins the profitability of the strategy, which is based on segmenting stocks into portfolios based on their 'streakiness' in earnings. A second double-sort-based strategy implemented by first sorting by the scale of the earnings changes and later on the length of the streaks of quarterly earnings surprises does reveal investors' exhibition of the gambler's fallacy, triggering earnings-based momentum in price. Subsequently, the authors embed the predictive power of streaks of earnings surprises into a possible new valuation metric which they term the 'streak factor'. The 'streak factor' is then deployed to explain the impact of successive earnings announcement results by examining the difference between returns earned by a portfolio of stocks enjoying a further quarterly earnings rise and a portfolio of stocks enduring a further quarterly earnings reversal. The streak factor explains more than half of the variation in the observed PEAD. The authors conclude that it is streaks of quarterly earnings surprises that explain PEAD and not simply the magnitude of quarterly earnings surprises or the reversal in earnings surprises.

5.2.4 Earnings uncertainty and company valuation

Earnings news is a numerical indication of the 'fundamental' company value, as opposed to the price. However, it also forms part of a broader 'valuation story' which companies, and especially their chief financial officers, tell the market (Holland 2004). Authors such as Zhang (2006a, 2006b) and Jiang *et al* (2005) devise empirical proxies to capture the degree of information uncertainty around stock value. The objective of both studies is to bring together evidence of the valuation implications of uncertainty concerning earnings outcomes. Such uncertainty reduces the degree of anticipation of announced earnings and hence exacerbates any response to earnings at the announcement date, when earnings uncertainty is partially or fully resolved. For more uncertain earnings announcements, investors need to work harder to assimilate the valuation implications of what is announced. Thus earnings-based anomalies thrive in these uncertainty-rich companies. Hence, it is possible to expect the most intense reactions as being to those earnings announcements that resolve the most uncertainty. This makes it important to control for earnings uncertainty in studying both the presence and persistence of earnings momentum around earnings announcements.

The six information uncertainty proxies suggested by Zhang (2006a) are company size as measured by the market capitalisation, company age, coverage by analysts and the

dispersion of analysts' forecast of earnings, the weekly excess stock return volatility of a company's stock, and the volatility of the company's cash-flows. High information uncertainty around earnings announcements gives a greater chance for biases in expectations to take hold and a sharper and stronger reaction to the resolution of the uncertainty such biases create. Each of these variables has featured in prior research concerning the market's response to earnings information. Hence the value of this study lies in the integration of much of what is already known into a coherent and comprehensive framework for conditioning any anomalous market response upon variables known to capture earnings uncertainty.

Asset price volatility has two aspects, and hence one may run the risk of conflating these two sources³⁶ of risk, since variance of a firm's signal about value, such as quarterly earnings, is characterised by the decomposition:

$$var(s) = var(v) + var(e) \dots \dots \dots (5.1)$$

where $var(s)$ denotes the variance of the signal about asset value and measures the overall amount of information uncertainty, $var(v)$ is the firm's underlying fundamental volatility and $var(e)$ captures the noise term reflecting the quality of information and the adequacy of earnings as a valuation signal in a market where many other factors hold sway (for example news about product innovation, technology and regulatory changes).

Zhang (2006b) motivates his analysis of information uncertainty and its effect on the intensity of various behavioural anomalies with reference to theoretical models within the 'noise trader' tradition which have served as the workhorse model of behavioural finance³⁷. In this chapter, I integrate the same concept of earnings uncertainty into the predictions of a model of the representative agent class, specifically the one by Rabin (2002b). By doing this, I hope to be able to generalise the applicability of this valuable area of empirical research.

5.2.5 Hypothesis development

Prior literature documents the impact of earnings announcements on stock market returns. A number of scholars have carefully tried to unravel the mystery behind the anomalies or regularities seen in stock returns just before and after company earnings announcements (see Chordia and Shivakumar (2006), Ball (1992)). What make research into some of those regularities so interesting are the persistent nature of the regularities and the profitability of some of the trading strategies based on them.

³⁶ See footnote 2 in Zhang (2006a)

³⁷ See examples in; De Long, Shleifer, Summers and Waldmann (1990b), Daniel, Hirshleifer, and Subrahmanyam (1998).

PEAD is the phenomenon which shows that stocks with positive earnings surprises continue to show positive drifts in returns following a good news earnings announcement, while stocks with negative earnings surprises continue to show negative drift in returns in the periods following their earnings announcement date. Some authors argue that this is a result of investors' underreaction to earnings announcements. In other words, at the arrival of quarterly earnings news, investors and other market participants fail to fully incorporate the information contained in the current earnings news into stock prices. Put another way, investors fail to fully grasp the valuation implication of the information contained in the current earnings news for future earnings forecasts. Hence, the error from their forecasting models is what triggers the observed mispricing in stocks. The larger the size of this forecast error, the larger the subsequent PEAD that follows. Based on the underreaction line of argument, Rabin (2002b) and Rabin and Vayanos (2010) theorise that the gambler's fallacy causes investors to underreact to trends. Investors underreact to trends because they expect trends to reverse rather than continue in the next time period. Investors expect the reversal of trend in order that the local distribution of earnings 'balances out' the opposing signal that has already been observed. This mistaken belief arises from the fact that the investors expect the observed sample of earnings signals to exhibit symmetry between positive and negative earnings surprise signals. In short, they succumb to the law of small numbers that the sample will exhibit all the characteristics of the population from which it is drawn. The failure of the earnings trend to reverse at the arrival of the most current earnings news causes the investor to underreact to the continuing trend. This investor underreaction to trends reinforces a continuation of trend in price rather than a reversal. Other theoretical models, such as the BSV model, posit that another form of cognitive bias known as the representativeness heuristic strengthens an investor's belief that an earnings trend will continue. This belief manifests by showing that investors extrapolate far into the future, which causes an overreaction to recently observed price trends. The BSV model posits symmetry between the two opposing regimes of a trend and mean-reversion. This implies that the investor, without any form of empirical evidence, incorrectly believes that the distribution of earnings surprises will show a distinct division between these two regimes. This introduces further error into the investor's forecasting model.

In studying PEAD, researchers employ different metrics as a measure of the earnings surprises or the information content of earnings news. The change in investors' earnings expectations at the arrival of quarterly earnings news, otherwise known as 'earnings surprise', provides the best measure of the earnings signal required for the study of PEAD (Ball and Bartov (1995), Foster *et al* (1984)). This is because, as the Rabin (2002b) and BSV (1998) models suggest, the sign of the previous earnings surprise will influence how

investors interpret the information contained in current earnings news. Some researchers employ earnings surprise as specified by analysts' forecasts, while others use realised prior quarterly earnings series to calculate the measure. There are a number of reasons why the former metric is preferred over the latter in the literature. One reason is that the earnings surprises calculated by the analysts' forecasts are less correlated than the realised earnings outcomes because analysts adjust their forecasts to incorporate earnings predictability. In addition to the reason above, I choose to employ the earnings surprise as defined by the analysts' forecast in this chapter because as this earnings surprise measure has been widely reported elsewhere in literature, analysts tend to follow those firms that are large, well-known, have established a reputation over the years, and have a track record of their stock performing well in the market. These characteristics are true of my S&P500 constituent companies sample frame, which is made up of stocks of large and very liquid companies and which almost certainly seed most money managers' funds. For investors chasing these stocks, analysts' forecast of earnings becomes the closest measure of investors' expectation of the quarterly earnings performance of these companies.

Although many studies examine the extent of the impact of earnings surprises as earnings signals on market returns, to my knowledge, only Loh and Warachka (2012) examine the empirical impact of streaks of earnings surprises on market returns. The authors do this by following the propositions of Rabin (2002b) of how the gambler's fallacy may influence investors if they observe streaks of earnings surprises. In one of their earlier works, Griffin and Tversky (1992) observe that individuals assign more weight to information in consistent multi-year patterns of either earnings rises or falls than to the information in mere isolated quarterly earnings news. This observation indeed gives more credence to the notion that streaks of earnings surprises might be a credible candidate to explain stock returns. The theoretical models of Rabin (2002b) and BSV are rather silent on the level of impact that individual quarterly earnings surprises have on return continuation. Both models, however, dwell heavily on the impact that the streaks of either positive or negative earnings surprises have on short-run return continuation.

In this chapter, the first two hypotheses examine the relation between streaks of earnings surprises, temporal reversals in earnings streaks and PEAD. The efficient market hypothesis states that public news about firms is instantaneously assimilated into the price. If relevant value information is assimilated into price instantaneously, then there will be no post-earnings announcement drift. Here I test whether there is significant association between streaks of earnings surprises and PEAD in one hand and temporary reversals in streaks of earnings surprises and PEAD on the other. Rabin (2002b) proposes a significant association

between streaks of earnings surprises and the PEAD. Following the above lines of argument, I derive the first and second hypotheses of this chapter as follows:

H₁: The streaks of earnings surprise and reversals do not have a significant impact on PEAD.

H₂: The streaks of positive (negative) earnings surprises do not have a positive (negative) association with PEAD.

In this chapter, I once more explore the propositions of Rabin (2002b) on how the gambler's fallacy impacts upon stock market returns by influencing a representative investor who employs the incorrect model in forecasting future earnings. This belief causes the investor to believe in a false premise of a likely reversal of a trend in the short term. Because he is quasi-Bayesian, he is unable to recognise his mistaken belief, which says that the model generating the process of earnings is static and that once a particular signal is drawn in the current period, the chance of drawing the same signal in the next period is reduced. The representative investor does not recognise that the earnings-generating process is a completely random process (at least in theory). The gambler's fallacy triggers underreaction in investors, which leads to the momentum (post-earnings announcement drift) exhibited by stock returns in the short run. However, since the gambler's fallacy can influence the investor, inducing him to make errors in predictions after observing short streaks of positive or negative earnings signals, it is crucial to see how this behaviour changes as the streaks grow even longer, hence the third hypothesis. It is important to know whether the representative investor in the Rabin and BSV models exhibits any form of learning as the streaks of earnings surprises lengthen, thus:

H₃: Short streaks of positive earnings surprises do not earn more positive abnormal returns than short streaks of negative earnings surprises. Long streaks of negative earnings surprises do not earn more significant abnormal returns than long streaks of positive earnings surprises.

Hypothesis 3 follows from the Rabin proposition that after the initial runs of positively correlated earnings surprises leading up to positive drift in returns, a correction phase follows which reverses the initial drift in positive or negative abnormal returns.

Furthermore, I examine the impact of information uncertainty on PEAD under the influence of the gambler's fallacy as the investor observes the lengthening streaks of positive or negative earnings surprises. At the quarterly earnings announcement, high information uncertainty will increase the level of underreaction from investors, while low information

uncertainty will do the reverse. This means that unconditional information uncertainty will have a negative correlation with returns – high uncertainty stocks yield lower future returns than low information uncertainty stocks (Zhang 2006a). In contrast to this, high (low) information uncertainty in the presence of a confirming streak of earnings surprises will see a larger (smaller) drift in returns than unconditional information uncertainty. Information uncertainty could be said to encompass any information which increases the level of ambiguity around the true value of any security. The investor searching through the financial statements of a firm has a mass of information to process and assimilate. This requires the investor to be able to interpret accurately what the financial figures actually represent in terms of firm value. Often, most of this information is hardly assigned any numerical value and the investor is saddled with the onerous task of making out what value should be assigned to the information in the companies' financial statements. Zhang (2006a, 2006b) documents that high information uncertainty exacerbates stock market underreaction and overreaction in the face of significant earnings news. I seek to examine the impact of information uncertainty on PEAD in the presence of lengthening streaks and temporary reversals of earnings surprises. I therefore put forward that:

H₄: Information uncertainty does not have a positive association with returns.

H₅: Conditional upon significant good or bad news, high (low) information uncertainty does not have a positive (negative) association with PEAD.

The nature of the interaction effect between information uncertainty and streaks of earnings surprises on PEAD will depend on a number of conditions. First, the nature of the information uncertainty variable involved is crucial. Increases in the information uncertainty variables such as age, analysts following, and firm size are expected to have an attenuating effect on PEAD. High levels of these information uncertainty proxies (age, firm size, and analysts following) unconditionally predict lower PEAD, since the ambiguity surrounding a company's value tends to diminish as these proxies of information uncertainty grow. On the other hand, rises in other idiosyncratic (specific) firm-level uncertainties such as the dispersion of analysts' forecasts, company cash-flow, and excess return volatilities exacerbate PEAD in the direction of the confirming earnings surprise. Information uncertainty reduces the degree of anticipation of announced earnings, inducing a larger earnings surprise at the earnings announcement date when that earnings uncertainty is resolved, thus:

H₆: Conditional upon streaks of earnings surprises, high information uncertainty does not exacerbate PEAD in the same direction as the confirming surprises. Therefore, high

information uncertainty conditional upon long streaks of positive (negative) earnings surprises does not produce a strong positive (negative) drift in returns.

H₇: PEAD trading strategies do not earn higher abnormal returns when streaks of positive earnings surprises are conditioned upon high information uncertainty stocks than on low-information uncertainty stocks.

5.3 Main empirical results

5.3.1 Sample descriptive statistics

Panels A to D of table 5.1 describe the variables of interest used in this chapter. Panel A provides the distribution of streaks of earnings surprises and temporary reversals across the sample period (1991 to 2006). A sequence of earnings surprises is defined as a streak if there are at least two consecutive earnings surprises of the same sign. On the other hand, a temporary reversal happens when a sequence of positive or negative streaks is terminated by the arrival of an earnings surprise of the opposite sign. The number of streaks across the entire sample ranges between 43% and 59% per year. This distribution clearly shows that streaks of earnings surprises are terminated more often in the sample of S&P500 companies when the earnings surprise metric is constructed using the difference between analysts' consensus of forecast of earnings for the next quarter and actual earnings figures. This is in sharp contrast to the distribution of sequences of EPS changes in chapter 4. Again, in contrast to what we see here, there are certainly more temporary reversals when compared to chapter 4, where changes in earnings expectations are constructed using the historical data of quarterly earnings realisations. Panel B reports the difference in firm's characteristics such as size, book-to-market, past returns, age, analyst coverage, stock volatility, and cash-flow volatility company/quarters characterised by streaks and those exhibiting temporary reversals of earnings surprises. The differences between the streak and reversal portfolios are statistically significant. This indicates that the impact of streaks on PEAD by far outweighs that of temporary reversals. These firm characteristics are used as information uncertainty proxies in later sections and measure the impact of information uncertainty on returns when conditioned on streaks of earnings surprises.

Panel C of table 5.1 shows more detailed descriptive statistics for the variables of interest. The Consistency variable consists of all of the negative and positive streaks of earnings surprises and temporary reversals. This table shows the longest positive and negative streaks to be of twelve quarters in length. BHAR is the three-day buy-and-hold Fama-French three-factor adjusted post-earnings announcement returns with a mean of 0.02% and a median of 0.01% which is an indication of a slight negative skewness in the distribution. The

US S&P500 index covers larger firms at the very top end of the US listed firms; however, there is a wide variation in the size of the individual constituent companies. The market capitalisation of the companies in my sample ranges from 2.40 million to 499 billion dollars. The age of the companies in the index ranges between one and twenty years. There is a balance of old and young companies in the index and this must be a result of the fact that qualifying new companies are added simultaneously to the index while old ones, falling below the acceptable performance threshold of the index, are deleted. Thus there is a gradual, if partial, churn in the constituents of the S&P500 index over time. The mean stock return volatility (SVOL) is 5% with a median of 3.7% per week.

Panel D shows the correlation coefficients matrix for the variables. The Pearson correlation is shown above the diagonal while the Spearman is shown below. BHAR and CONSISTENCY have a substantial positive correlation (Pearson = 0.13 and Spearman = 0.12). This indicates a positive relation between PEAD and streaks of earnings surprises. The correlation coefficients between company size, analyst coverage, and company age are all positive, and this may be an indication that they capture the same type of information. Weekly stock return volatility (SVOL) and analyst forecast dispersion (AFORD) have a positive correlation (Pearson = 0.002 and Spearman = 0.16) and a weak positive correlation with cash-flow volatility (CVOL) (Pearson = 0.01 and Spearman = 0.01).

5.3.2 The distribution of streaks of earnings surprises and temporary reversals

Table 5.2 and figure 5.1 show the frequency distribution of streaks of negative and positive earnings surprises among the S&P500 constituent companies sample. The table shows a distribution consisting of 51% positive and negative streaks and 49% temporary positive and negative reversals. From table 5.2, within the streaks of earnings surprises, 67.85% are positive streaks whereas a considerable lower number (32.15%) are negative streaks. This distribution follows a similar pattern to that seen in chapter 4. My S&P500 sample companies obviously report continuations in quarterly EPS rises far more than they report continuations in quarterly EPS falls (continuations in positive earnings surprises are more than double the number of continuations in negative earnings surprises). Table 5.2 shows that reporting of long streaks of earnings surprises is less dramatic when earnings surprises are calculated using analysts' forecasts than when historical quarterly earnings are used. Only 2.72% of my sample companies report positive earnings surprise streaks extending to twelve quarters. Even fewer companies report declines in quarterly EPS for twelve consecutive quarters (0.4% of the total sample companies). This is not surprising, as companies that report declining quarterly EPS for three years or more are likely to be deleted from the index and may face bankruptcy. The trend here shows that companies which persistently report rising

or falling streaks in quarterly EPS are less dramatic and such streaks are shorter than seen in chapter 4. Still, a considerable number of companies report positive streaks of earnings surprises of between two and six quarters in length. This is more than negative streaks of the same lengths reported over the same period. Interestingly, this table and figure 5.1 show that 49% of the time, companies report temporary negative and positive reversals. Again, this indicates that with analyst forecasts, information about the true meaning of earnings is incorporated into the price more quickly and accurately, hence there are more streak reversals when compared with the historical earnings metric, which shows more continuations than reversals. There are 52.1% negative reversals (when a growing streak of negative earnings surprises is terminated by the most recent positive earnings surprise) and 47.9% positive reversals (when a growing trend of positive earnings surprise ends). It is evident from the above that the sample companies are more likely to reverse a negative trend than a positive trend. Various authors argue that there are a number of reasons why firms seem to report more earnings rises than falls. Some researchers believe that this high likelihood for firms to report quarterly EPS rises may be a result of earnings management by managers to meet or beat current analysts' earnings expectations³⁸. Others believe that analysts receive incentives from managers and therefore their forecasts of earnings are more likely to be kept 'intentionally' low so as to create a positive earnings surprise at the earnings announcement date. Here earnings expectations are managed down to induce a share price bounce on the day on which earnings beat analysts' deflated expectations. The resulting streaks of positive earnings surprises generate earnings momentum in stock returns for such companies³⁹. In other words, as documented in the literature, markets reward companies with earnings outcomes which continually beat the analysts' forecasts of earnings more than other companies with the same level of earnings forecast error but which failed to meet expectations⁴⁰. Loh and Warachka (2012) reports that earnings surprises streaks of more than ten quarters are not frequent in their sample's distribution of streaks. This is consistent with the findings in the distribution of my sample earnings surprises streaks.

Although there is a clear similarity between the distributions of streaks of earnings surprises in this chapter and the distribution of sequences of EPS changes in chapter 4, there are some clear distinctions between them. In chapter 4, there are far more positive continuations in EPS changes than there are reversals while in this chapter, there are more positive continuations in earnings surprises than negative continuations. Besides that, there are far

³⁸ See Bartov, Givoly and Hayn (2002), Kross, Ro and Suk (2011).

³⁹ See Chan, Karceski and Lakonishok (2007), Cen, Hilary and Wei (2013).

⁴⁰ See Bartov, Givoly and Hayn (2002).

more temporary reversals in earnings surprises when analysts' forecasts of earnings are used in constructing the earnings surprise metric.

5.3.3 PEAD, streaks of earnings surprises and temporary reversals

Figure 5.2 shows a plot of the mean of three-day PEAD returns against the Consistency variable. The figure shows that Consistency in the sign of earnings surprises explains three-day buy-and-hold abnormal returns around the quarterly earnings announcement date. I test hypotheses 1 and 2 in this section to examine the relation between streaks of earnings surprises, temporary reversals, and the PEAD drift in the three days around earnings announcement date. The tests are shown in 13 different regression models in table 5.3. The results in table 5.3 show that in all the models tests, streaks of earnings surprises in my S&P500 sample explain the three-day buy-and-hold Fama-French three-factor adjusted returns around the earnings announcement date. The table results show that even in multivariate regression with other covariates, the streaks of earnings surprises maintain their explanatory power for PEAD. By increasing the length of the streaks of earnings surprises by one unit, PEAD returns increased by 0.21%, and this is statistically significant at the 1% confidence level. This result is consistent with the finding of Loh and Warachka (2012). There is no significant relationship between the magnitude of earnings surprises and the PEAD drift across the models tests here. This finding is consistent with both the BSV (1998) and Rabin (2002b) models which state that it is the sequences of earnings surprises rather than their magnitudes that investors look at to extract information about earnings at earnings announcement. In table 5.3, model 3 shows Consistency in earnings surprises (which is a proxy containing the sequences of all the streaks and temporary reversals in earnings surprises in the most recent quarter) and the magnitude of earnings surprises (ESURP) as covariates; Consistency explains 0.018% (t-value = 2.09) of the three-day buy-and-hold abnormal returns, while ESURP explains just 0.011% (t-value = 0.54) of the abnormal returns, which is insignificant. Again, this result shows that various lengths of earnings streaks and temporary reversals are far better explanatory variables than mere magnitude of quarterly earnings surprises. However, in model 4 of the same table, Consistency in earnings surprises loses its explanatory power in a multivariate regression with the streaks of earnings surprises. Again, this suggests that in explaining PEAD returns, the length and the sign of earnings surprises streaks are more important than temporary reversals. Investors react differently to streaks of positive earnings surprises and streaks of negative earnings surprises. Investors also perceive short streaks as 'surprises', hence their strong price reactions, while responses to longer streaks are more muted. From table 5.3, it is evident that the streaks in earnings surprises show a positive relation with PEAD in all of the

models tests. This finding is consistent with the finding of Loh and Warachka (2012), who report that trading strategies based on streaks of earnings surprises are profitable.

In models 8 and 9 I also test for the impacts of positive and negative streaks on PEAD respectively. From the results, S&P500 companies with a minimum of positive earnings surprises in two consecutive quarters earn an abnormal return of 0.25% (t-value = 3.34), which is statistically significant at a 1% confidence level. On the other hand, companies with negative streaks in earnings surprises earn a negative three-day abnormal return of -0.10%. Although this performance by companies with negative streaks of earnings surprises is statistically significant at a 10% level, they are much more muted when compared with those of companies with positive streaks in earnings surprises. This finding is also related to the findings of Loh and Warachka (2012), who observe that trading strategies that buy stocks with positive streaks in earnings surprises and sell stocks with negative surprises in earnings surprises are profitable. When a positive (negative) streak in earnings surprises is terminated by the arrival of a negative (positive) earnings surprise in the most recent quarter, a positive (negative) reversal occurs. S&P500 companies that break their positive earnings surprises streaks by reporting a negative earnings surprise earn negative three-day buy-and-hold Fama-French three-factor adjusted post-earnings announcement returns of -0.18%, which is highly significant at a 1% confidence level. This finding is consistent with that reported in Bartov, Elliott, and Finn (1999). On the other hand, companies with negative reversals in earnings surprises also earn negative abnormal returns which are statistically significant but more muted than returns from positive reversals. This finding contradicts the findings of Loh and Warachka (2012) that reversals in earnings surprises do not significantly explain stock returns. The reason for this difference in findings between my work and that of Loh and Warachka (2012) may lie in the type of sample used. My S&P500 sample comprises companies that have high market capitalisation and are highly liquid. They have large numbers of analysts and investors following them. It is therefore not surprising to see that the market's reactions are almost instantaneous when streaks of earnings surprises are terminated. Companies in which positive streaks are terminated at the most recent earnings announcement date seem to receive a negative reaction from the market. On the other hand, companies that turn a leaf with a positive earnings surprise in the most recent earnings announcement date do not attract such a dramatic reaction from the market. The markets seems to underreact more when a negative streak in earnings surprises is terminated than when a positive streak in earnings surprises is terminated. This behaviour is likely to be related to one of the key assumptions of the BSV (1998) model, which is that investors believe that negative trends in earnings are less likely to reverse. Investors under the gambler's fallacy also wrongly believe that a particular trend will continue, therefore any

reversal that occurs in the future (trend) is adjudged to be transitory. In models 3 and 6, I find no significant relation between the interaction parameters of Consistency in earnings surprise and the recorded magnitude of the earnings surprise, and the PEAD. There is also no significant relation between the interaction parameters (of streaks of earnings surprises and magnitude of earnings surprises) and PEAD in models 7, 12, and 13.

5.3.4 The impact of various lengths of streaks of earnings surprise on PEAD

In section 5.3.3 above, the various test analyses show that streaks of earnings surprises explain the three-day Fama-French three-factor adjusted returns. In this section, I test hypothesis 3 to understand how investors and the market respond to lengthening streaks of earnings surprises. Also, as discussed in section 5.2.2, various papers in the literature document⁴¹ that companies that report increasing earnings (quarter on quarter) enjoy market goodwill, while companies with continuous declining quarterly earnings seem to be punished by the market with a decline in their share price. It is therefore pertinent to investigate this investor behaviour towards different streak lengths around the quarterly earnings announcement. This will give a better insight into the informativeness of earnings surprise streaks around the earnings announcement date.

I begin this section by analysing the various impacts of lengthening of positive and negative streaks of earnings surprises on PEAD. I test three models each in panel A and B of table 5.4 to examine the impacts of streak lengths of positive and negative earnings surprises respectively on PEAD. Panels A and B of table 5.4 show the results of the effect of lengthening positive and negative streaks of earnings surprises. The results here support the propositions of Rabin's (2002b) and Rabin and Vayanos' (2010) models. In panel A, shorter sequences of positive streaks of earnings surprises of between two and four quarters seem to trigger positive PEAD in my S&P500 companies sample (0.023% with t-value = 7.72). However, when positive streak lengths grow to between five and eight consecutive earnings surprises, the intensity of the underreaction becomes weaker. Although the level of three-day Fama-French adjusted returns generated is still positive and significant (0.011% with t-value = 3.65), it is less significant than that generated by short streaks of between two and four quarters. As the streak lengthens even further to between nine and twelve quarters, the impact of the streaks upon abnormal returns becomes muted and is not statistically significant. In panel B, I test the impact of lengthening negative streaks of earnings surprises on PEAD. The results follow the same pattern seen with the different lengths of positive streaks, albeit with the opposite impact on the three-day abnormal returns. Short streaks of negative earnings surprises of lengths of between two and four quarters generate a

⁴¹ See Myers, Myers, and Skinner (2007).

significant negative abnormal return (-0.001% with t-value = -2.24). Further lengthening of negative streaks of between five and eight quarters generate PEAD returns that are still negative and more statistically significant (-0.003% with t-value = -3.89). Finally, companies reporting falling earnings outcomes consistently for nine to twelve quarters generate positive and statistically significant abnormal returns (0.009% with t-value = 6.76). One point is clear from the results in panel A and B of table 5.4: the market and investors seem to reward companies that report positive earnings surprises and punish those that report negative earnings surprises. The results also seem to suggest that there is some learning going on as investors observe lengthening streaks of positive and negative earnings surprises. Companies reporting long streaks of positive earnings surprises may run the risk of losing some of their integrity in the likely event that investors are no longer 'surprised' when there is yet another positive earnings surprise when the quarterly earnings are announced. For the companies that fall into this category, investors do not struggle to work out the true value of their earnings and its subsequent impact on prices in the days and weeks following the earnings announcement date. This may be the reason why abnormal returns to streaks of positive earnings surprises of nine quarters and longer generate muted and statistically not significant returns. On the other hand, companies reporting declining earnings consistently for nine quarters and longer seem to pay a premium to investors holding on to their stocks. These results confirm my third hypothesis. This makes sense, as the liquidation risk faced by this sub-sample of firms must be seen as considerable by their remaining equity investors.

The results are consistent with the gambler's fallacy effect of Rabin's (2002b) model and hot-hand fallacy of Rabin and Vayanos' (2010) model. Short streaks generate significant PEAD, while a reversal in returns is triggered by longer streaks of earnings surprises. Loh and Warachka (2012) report a different behaviour in the response of stock returns to lengthening streaks of earnings surprises. The authors report that the response of stock returns to increasing lengths of streaks of earnings surprises intensifies as the streaks grow longer. The authors posit that the effect of the gambler's fallacy on investors seems to persist, as investors are confident that the streaks they observe will continue. The authors also report that the response of PEAD to the streak length does not support the claims of Rabin and Vayanos (2010), who propose that this behaviour is a result of the hot-hand fallacy opposing the gambler's fallacy.

Panels C and D of table 5.4 show parallel results (tests for robustness) from the pooled OLS regressions and these support my initial results in panels A and B of table 5.4 respectively. The results reported in both panels A and B are obtained from a panel data regression analysis.

5.3.5 PEAD and information uncertainty

In this section, I test hypothesis 4 and examine the relation between PEAD and information uncertainty. The different levels of proxies for information uncertainty surrounding the fundamentals of stocks around earnings announcement dates are sorted into five quintile portfolios with two extremes of high and low information uncertainties. The portfolio of high (low) information uncertainty stocks includes those stocks that have large (small) ambiguity surrounding their true values at earnings announcement dates. Usually, high (low) information uncertainty stocks are those with small (large) analyst following, small (large) firm size, i.e. based on market capitalisation, young (old) companies, large (small) dispersion in analysts' forecasts, high (low) stock return volatility, and high (low) cash-flow volatility. Table 5.5 shows the results of a one-way sort based on a three-day abnormal return by information uncertainty proxies. I sort the stocks into five portfolios with stocks of low (high) information uncertainty at the top (bottom) of the table. The results show that portfolios of high information uncertainty stocks have lower average abnormal returns than portfolios of low information uncertainty stocks. The average zero-investment portfolio (high quintile – low quintile) return of -0.013% (t-value of -0.88) is negative and not statistically significant. My result here is consistent with the finding of Zhang (2006a) who also points out that Jiang *et al* (2005) report statistically significant negative results for similar tests. Zhang (2006a) attributes the disparity between his finding and that of Jiang *et al* (2005) to the difference in the holding period of portfolios in the two studies. Zhang posits that a portfolio with a longer holding period most likely will yield a negative and significant result as the initial market response unwinds in the long term. From table 5.5, all of the trading strategies that are long in stocks of high information uncertainty and short in stocks of low information uncertainty produce negative and not statistically significant abnormal returns. The reason for this might be that the arrival of earnings news brings about a partial resolution of the uncertainties surrounding a company's fundamental value; hence there is no dramatic price response from high uncertainty stocks. Therefore unconditional low uncertainty stocks have higher returns than unconditional high uncertainty stocks. As Odean (1998) observes, investors usually overestimate prices when information about them is inconclusive. Zhang (2006a) also further argues that the evidence showing that low information uncertainty stocks have higher future returns than high information uncertainty stocks does not support the argument that information uncertainty is a cross-sectional risk factor that needs to be compensated for with higher returns. Diether *et al* (2002) and Boehme *et al* (2006) both argue that information uncertainty may lead to divergence of opinion among investors, which could lead to further mispricing. Consistent with my results here, Diether *et al* (2002) report that using dispersion in analysts' forecasts and stock return volatility as proxies, high uncertainty stocks earn

future lower returns than low uncertainty stocks. The authors use analysts' earnings forecast dispersion as a proxy for differences in opinion amongst investors about a stock.

In order to further establish that there is post earnings announcement drift in my sample; I employ another metric. I use the metric (MRET) which is a cumulative past eleven months stock returns. I use this metric because it captures the drift in price (returns) generated by the earnings news. The results are shown in column 8 of Panel A in table 5.5. I sort stocks into five portfolios based on the previous 11-month cumulative returns showing extreme past loser and winner portfolios in the low and high deciles respectively. The past winner portfolio outperforms the past loser portfolio by a margin of 0.126% (t-value of 6.66) in the three-day buy-and-hold Fama-French 3-factor model adjusted returns. This further strengthens my argument of existence of PEAD in returns.

5.3.5.1 PEAD, information uncertainty, and streaks of earnings surprises

The evidence in the finance literature shows that information uncertainty conditional on the nature of news has a positive correlation with post-news drift. Zhang (2006a) reports that post-news price drift increases with information uncertainty for good news events. Using news-based proxies (such as analyst forecast revisions and past stock returns), the author shows that under the influence of information uncertainty, good news stocks earn higher returns than bad news stocks. The author also show that a trading strategy that buys (sells) good (bad) news/high information uncertainty stocks is more profitable than an alternative strategy that buys (sells) good (bad) news/low information uncertainty stocks. I test hypothesis 5 in this section.

Following Zhang's (2006a, 2006b) procedures, I choose the same information uncertainty proxies, such as a firm's market capitalisation (MV), age (number of years since a company was added to the S&P500 stock index), analyst coverage (ACOV) (number of analysts following a firm), analyst forecast dispersion (AFORD), company's cash-flow volatility (CVOL), and the company's weekly excess stock volatility (SVOL). However, in a slight departure from Zhang's (2006a, 2006b) procedure, I test for the impact of information uncertainty on the returns of companies with positive and negative streaks of earnings surprises over twelve quarters around the most recent earnings announcement date. Here, good news companies are those with confirming positive streaks in earnings surprises in the most recent quarterly earnings announcement, whereas the reverse is true for bad news companies. I test for the extent of the influence of high and low information uncertainties by allowing for interaction between each of them and the positive and negative earnings surprises streaks. I also test for the profitability of trading strategies that are based on high and low information uncertainties conditional upon positive or negative streaks of earnings

surprises as separate discrete characteristics. I start by sorting my sample stocks into those with positive and negative earnings surprise streaks. Subsequently, I sort each of the two groups of stocks into those of high and low information uncertainty. The median of each of the information uncertainty proxies is used as a cut-off point between low and high information uncertainty. Information uncertainty values above (below) the median value are treated as high (low). Table 5.6 shows the result of the test analyses.

The results in table 5.6 show that information uncertainty when conditional upon the nature of news is positively correlated with returns around earnings announcement dates. This follows an exactly similar pattern to those we see in other studies in the finance literature. The 'news' in my case here is the confirmation of either a continuation of a positive or negative streak of earnings surprises, or otherwise, at the earnings announcement date. However, the relation as shown in the results of table 5.6 slightly differs from Zhang's (2006a) results. This disparity between my results and Zhang's particularly occurs when the information uncertainty proxies interact with positive streaks of earnings surprises. The double sort of the PEAD returns by information uncertainty proxies and positive streaks of earnings surprises show a marked increase in three-day abnormal returns. Sorting by companies' market capitalisation (market value) and positive streaks of earnings surprises show that lowly capitalised companies (high information uncertainty companies) generate three-day abnormal returns of 0.038% (t-value = 3.45) while low information uncertainty companies (large capitalised companies) generate not statistically significant abnormal returns of 0.0008%. Similarly, sorting by company age and positive streaks of earnings surprises shows that high information uncertainty stocks generate three-day abnormal returns of 0.040% (t-value = 3.65) while low information uncertainty companies generate not statistically significant three-day abnormal returns of 0.005%. Sorting by analyst coverage of companies and cash-flow volatility with positive streaks of earnings surprises, high uncertainty stocks generate statistically significant three-day abnormal returns of 0.027% (t-value = 2.37) and 0.031% (t-value = 2.43) respectively. However, sorting both weekly excess stock return volatility and analysts' forecast dispersion by positive streaks of earnings surprises, high uncertainty stocks generate positive, but not statistically significant, three-day abnormal returns of 0.012% and 0.021% respectively.

Sorting the information uncertainty proxies with streaks of negative earnings surprises shows no discernible pattern. Amongst the six information uncertainty proxies employed, only market capitalisation, cash-flow volatility, and analyst coverage (proxying for high information uncertainty) generate positive and statistically significant three-day abnormal returns with streaks of negative earnings surprises. The reason why streaks of negative earnings surprises under the influence of high information uncertainty earn positive abnormal returns

could be that investors who hold onto the stocks of these companies with declining earnings for many quarters can exert a premium for the liquidation risk they must increasingly bear. An interesting finding here is that none of the trading strategies involving buying (selling) high (low) information uncertainty stocks with negative streaks of earnings surprises is profitable, suggesting that once we control for common risk factors, informational arbitrage (based on these six information uncertainty proxies) is ineffective within the S&P500 during my sample period.

Employing trading strategies that buy (sell) high (low) uncertainty stocks with streaks of positive earnings surprises generates positive and statistically significant three-day abnormal returns only when age and market capitalisation are used as information uncertainty proxies. Other trading strategies involving buying (selling) high uncertainty stocks with positive (negative) earnings streaks earn not statistically significant positive abnormal returns. However, those involving buying (selling) low uncertainty stocks with streaks of positive (negative) earnings surprises earn negative abnormal returns with all of the six information uncertainty proxies, but this is only statistically significant when market capitalisation and age are used as proxies for information uncertainty.

The above results could be interpreted in a number of ways. First, it seems that to the investors in the S&P500 companies, the two most important factors determining the degree of information uncertainty reflected in a sample company's stock returns are the number of years the company has 'survived' in the index and the company's size. Before being admitted into the index, companies have to pass rigorous benchmark performance indicators⁴² and have to stay above the index's acceptable performance thresholds in order to remain within it. It seems that investors view favourably those companies that stay within the index for a considerable length of time. This is a form of the well-known 'familiarity breeds investment' principle or what the psychologists Gerd Gigerenzer and Daniel Goldstein denote as the 'recognition heuristic' in their 2002 paper. Additionally, it is well established in the research literature that investors have a favourable outlook on companies with large market capitalisation. So for the S&P500 companies, market capitalisation, length of the time the company has stayed in the index, extent of the volatility of a company's cash-flow, and number of analysts following a firm seems to be the major source of high information uncertainties towards their stock market performance around quarterly earnings announcement dates. Little or no information is available on companies of low market capitalisation, young firms in the index, and those with low analyst coverage, and this leads to high uncertainty with regard to their fundamental values. However, this sub-set of

⁴² See Chan, Kot, and Tang (2013).

companies also receives a higher level of resolution of their uncertainties at earnings announcement dates than low uncertainty stocks. Investors respond to this resolution of uncertainty with much intensity, and this exacerbates earnings-generated momentum in price.

5.3.5.2 PEAD, information uncertainty, and lengthening streaks of earnings surprises

In section 5.3.5.1 above, I sort PEAD returns by both information uncertainty and by streaks of either positive or negative earnings surprises. However, here I test hypotheses 6 and 7 in an attempt to better understand how different lengths of streaks interact with the information uncertainty proxies around earnings announcement dates. Here, I sort information uncertainty proxies by different lengths of streaks of positive or negative earnings surprises. The analysis below is expected to validate the results of the analysis in section 5.3.5.1.

I begin by testing the impact of information uncertainty and streaks of earnings surprises (positive or negative) running consecutively for two to four quarters, two to eight quarters, and nine or more quarters on three-day PEAD returns. The results are shown in panels A, B, and C of table 5.7 respectively. Sorting high uncertainty stocks with positive streaks of two to four quarters, generates positive PEAD returns that are only statistically significant when market capitalisation and age serve as information uncertainty proxies. All other four proxies generate statistically not significant PEAD returns. However, sorting with high information uncertainty and negative streaks of earnings surprises of between two and four quarters generates returns that are not statistically significant, except when analyst coverage is used as the information uncertainty proxy. A trading strategy that buys (sells) high (low) information uncertainty stocks of between two to four streaks of earnings surprises generates mostly negative returns that are not statistically significant except when market capitalisation is employed as the uncertainty proxy. When high information uncertainty stocks are sorted by positive streaks of between two and eight quarters, larger statistically significant positive PEAD returns are generated than what was seen in section 5.3.5.1. Sorting by market capitalisation and positive streaks of earnings surprises of between two and eight quarters, high uncertainty stocks generate statistically significant positive three-day abnormal returns of 0.046% (t-value = 3.71). Similarly, sorting by age, analyst coverage and cash-flow volatility, high uncertainty stocks generate statistically significant positive abnormal returns of 0.047% (t-value = 3.94), 0.029% (t-value = 2.31), and 0.035% (t-value = 2.37) respectively. The magnitude of the abnormal returns seen here is more than that generated when information uncertainty is not conditioned on the length of the streaks of earnings surprises. Sorting high uncertainty stocks with negative streaks of earnings surprises of between two and eight quarters in length follows an almost identical pattern (both in terms of

the sign and size of the abnormal returns) to the results obtained in section 5.3.5.1. Sorting by market capitalisation, analyst coverage, cash-flow volatility and streaks of negative earnings surprises of between two and eight quarters, high uncertainty stocks generate statistically significant positive abnormal returns of 0.036% (t-value of 2.0), 0.041% (t-value = 2.56), and 0.041% (t-value = 2.25) respectively.

It is clear from the results that the impact of the gambler's fallacy grows with the lengthening of the streaks of earnings surprises. As the streaks in earnings surprises continue to lengthen in a particular direction, in the presence of information uncertainty, the gambler's fallacy causes PEAD returns to intensify. This is evident from the increase in PEAD returns when streaks of two to eight quarters are used as against streaks of two to four quarters. The gambler's fallacy causes the representative investor to underreact to lengthening streaks of earnings surprises at successive announcement dates.

A completely different picture is painted when high uncertainty stocks are sorted by positive streaks of earnings surprises of nine or more quarters in length. Sorting by all the information uncertainty proxies generates positive, but not statistically significant, three-day abnormal returns except when using age as an uncertainty proxy, which generates negative and not statistically significant abnormal returns. Sorting with negative streaks of nine or more quarters earns similar results to those of positive streaks of the same lengths. This finding about the relation between long streaks of earnings surprises and abnormal returns in the presence of high uncertainty shows that the impact of the gambler's fallacy, as predicted by Rabin (2002b), is quite muted when investors have diffuse priors, as would indeed characterise a highly uncertain stock market valuation.

It does seem that uncertainties about S&P500 companies persist more when there are increasing positive streaks of quarterly earnings surprises for up to eight quarters. However, beyond eight quarters to nine and more, the interaction effect between information uncertainty and streaks of earnings loses its explanatory ability. One possible explanation is that continuing streaks of both positive and negative earnings surprises bring about little surprise to investors and most likely uncertainties surrounding the value of such companies will have been fully or significantly resolved after similar earnings news has been received consecutively for more than eight quarters. The arrival of a continuous stream of affirmatory quarterly earnings news would normally dissipate some of the uncertainties surrounding a stock's value; however, a growing trend in streaks (up to eight quarters of consistency in the sign of the earnings surprise) at earnings announcement negates this effect by instead introducing more uncertainty into the true value of the stocks. The impact of information uncertainty on PEAD drift is more defined when its interaction with different lengths of

earnings surprises is taken into account. So information uncertainty and 'streakiness' have incremental, not substitutive, value in explaining PEAD.

5.4 Robustness checks

In this section, I employ alternative model specifications and competing hypotheses to show the robustness of the results in the main empirical results section above. In order to achieve this purpose, I employ analysts' forecast revision, which is often used as a measure of the change in investors' expectations of quarterly earnings (or earnings surprise) in the literature. I carry out this robustness check in two different ways: first by establishing that the sign and size of analysts' forecast revision can proxy as an earnings surprise measure and second, by establishing that the behaviour of investors in the presence of analysts' forecast revisions and information uncertainty around earnings announcement dates produce similar results to those obtained when other proxies of earnings surprise are used.

5.4.1 PEAD and analysts' forecast revision

In the finance literature, analysts' forecast revisions are one of the proxies used to measure earnings surprise. In chapter 3, I introduced the analyst forecast revision and showed how it is constructed and used as a measure of earnings surprise. Here I use it as an alternative measure of earnings surprise for my S&P500 constituent companies and use it to explain earnings-generated momentum in price.

In table 5.8, I present the results of a one-way sort of PEAD returns by the current analyst forecast revision, again to confirm the existence of PEAD in my sample companies' returns and the presence of cognitive bias amongst investors. The confirmation of the existence of PEAD in my sample stocks is important for two major reasons. First, it refutes the argument that PEAD can only exist in stocks of small and illiquid companies and therefore could be attributed to compensation for risk. Second, using streaks of earnings surprises as the earnings momentum metric, it reinforces the propositions of Rabin (2002b) and BSV (1998) that an investor's behaviour is influenced when he observes streaks of earnings surprises over a period of time. As the two models posit, this behaviour reinforces earnings-generated momentum in price.

I classify analysts' forecast revisions into three different groups: good news, bad news, and no news. If the revision is a rise in expected earnings, I recognise it as positive and classify it as good news, whereas if the revision is a fall in expected earnings, I recognise it as negative and classify it as bad news. If the difference between the most recent analysts' forecast revision and the immediate past revision is zero, I classify it as no news. My sample

data constitutes of 21.24%, 53.05%, and 25.71% of negative, zero, and positive analysts' forecast revisions respectively. Again, the nature of the distribution of analysts' forecast revisions reveals a similar pattern to that seen with the forecast error in the main empirical sections, which suggests that analysts more readily give revisions that are low enough to give positive surprises. This is because, as this distribution shows, positive revisions in analysts' forecasts of earnings are more frequent than negative revisions. This observation is consistent with the extant literature. The bad news companies have three-day abnormal returns of 0.001% (t-value = 0.16), zero news companies have 0.01% (t-value = 1.07), and good news companies have 0.03% (t-value = 4.45). A trading strategy that goes long on good news companies and short on bad news companies generates a spread of 0.029%, which is statistically significant (t-value = 3.90). The result confirms that bad news companies earn lower future returns, while good news companies earn higher future returns. Again, this is consistent with past reported findings in the analyst forecast revision literature. This result is also consistent with the interpretation that investors underreact to new earnings information, since future movements in stock prices are in the same direction as the most recent earnings surprise.

5.4.2 PEAD, information uncertainty, and analysts' forecast revisions

In table 5.9, I test the relation between information uncertainty and the nature of news, using analysts' forecast revision as a proxy for investors' response to news about corporate earnings. In each case, I sort stocks by my information uncertainty proxies into two categories of high and low uncertainties using the median as a separation point. The stocks are first sorted into three different categories based on their most recent analyst forecast revision. Each of the stocks is sorted into one of the three portfolio categories; bad news, no-news, and good news. Only results for the bad news and good news portfolios are reported here.

The result in table 5.9 follows the same pattern as that in table 5.6. Here again, the proxies of information uncertainty used in section 5.3.5.1 are employed. In each case, higher information uncertainty generates larger three-day abnormal returns for good news portfolios than for bad news portfolios. In a double sort by positive analysts' revisions and information uncertainty proxies, high information uncertainty portfolios generate larger abnormal returns than low information uncertainty portfolios. This behaviour is shown, for example, with the MCAP proxy, where the good news portfolio of high information uncertainty stocks generates a three-day abnormal returns of 0.058% (t-value = 2.66), while the low information uncertainty portfolio generates returns of 0.009%, which is not statistically significant. On the other hand, the bad news portfolio of high information uncertainty stocks generates

abnormal returns of 0.018%, while the portfolio of low information uncertainty generates abnormal returns of -0.013%. In the good news group and using market capitalisation as the information uncertainty proxy, a trading strategy that invests long in high uncertainty stocks and sells short in low uncertainty portfolio generates an abnormal return of 0.061% ($t = 2.17$). In the bad news group, this strategy generates an abnormal return of 0.032% (t -value = 1.98). For the good news strategy, only the MCAP, CVOL, SVOL, AFORD, and ACOV information uncertainty proxies generate positive and statistically significant abnormal returns. For the bad news strategy, only the CVOL proxy generates statistically significant abnormal returns.

A common observation here is that a company's market capitalisation appears to be an important proxy for information uncertainty for good news companies. With market capitalisation as an information uncertainty proxy, high uncertainty companies represent the group of the smallest companies with the S&P500 index. From the results, investors respond more strongly to this sub-sample of companies when they have good news, hence the high abnormal returns. One can therefore conclude that investors underreact more to smaller companies with good earnings news in the S&P500 index, despite the fact that these smaller members may be amongst the largest companies traded in the market. This also confirms results reported by Zhang (2006a) in which the author documents that because of this kind of underreaction, small firms generate lower returns following bad news than following good news. Another observation is that investors appear to underreact to good news companies with high cash-flow volatility. The portfolio of high cash-flow volatility stocks generates a three-day abnormal return of 0.058% (t -value = 3.25). A good news trading strategy based on taking a long (short) position on high (low) cash-flow volatility stocks generates a statistically significant three-day abnormal return of 0.062% (t -value = 2.23). For all of the portfolios, the good news companies with high information uncertainty generate larger abnormal returns than bad news companies and show more PEAD.

5.5 Summary and conclusion

In this chapter, the case for the informativeness of the streaks of earnings surprises first examined in chapter 4 is further strengthened. This is done by investigating the explanatory power of streaks of earnings surprises in a short window of three days. This window falls within that period when the effect of the nature of earnings news is most intense in the stock market, especially for large companies like my S&P500 companies. The results show that even in this short window, investors in S&P500 companies appear to be influenced by the confirmation (or otherwise) of the lengthening of negative and positive streaks of earnings surprises at the most recent quarterly earnings announcement. This further supports my

hypothesis that investors underreact to streaks of changes in their expectations about stock returns. The impact of streaks on returns is further strengthened in the presence of high information uncertainties. This interaction effect between streaks of earnings surprises and high information uncertainty is most intense when information uncertainty proxies such as market capitalisation, age, and cash-flow are used. Therefore the influence of the gambler's fallacy on the representative investor in the presence of information uncertainty becomes more pronounced with increasing lengths of streaks of earnings surprises.

When the distribution of earnings surprises in this chapter is compared with that in chapter 4, one point is obvious. There are far more temporary reversals in earnings surprises in this chapter than in chapter 4. The only possible reason for this could be the use of analysts' forecast of earnings as a measure of investors' earnings expectations. The presence of more temporary reversals here would generally reduce the intensity of the impact of the continuation in earnings surprises on price movements. Changing my model for calculating the change in investors' expectations (in chapters 4 and 5) brings to the fore the implications that this choice may have for the reported results. Also the result from using an alternative model specification, viz; using analysts' forecast revisions to represent the nature of earnings news and how that is revealed in stock prices, shows the robustness of my previous test analyses with streaks of earnings surprises when those surprises are measured by successive quarterly earnings forecast errors.

Table 5.1

Panel A reports the summary statistics of the sample of quarterly earnings surprises, streaks, and temporary reversals of quarterly earnings surprises. The streaks and reversals are defined by the quarterly earnings surprises (ESURP). ESURP is the quarterly earnings surprise calculated as the I/B/E/S actual quarterly earnings minus the most recent consensus mean analysts' earnings forecast scaled by prior year end stock price. A streak of quarterly earnings surprises occurs when at least the two most recent earnings surprises of my sample company are of the same sign (i.e. a continuation of quarterly earnings rises or falls). However, a temporary reversal of earnings surprises occurs when a streak is terminated. Year is my sample period beginning from January 1991 to December 2006. For each of the sample years, the average ESURP in my sample is reported along with the average firm size (MCAP – in millions of dollars) of the S&P500 companies in my sample. The number of streaks and reversals, and the percentage of streaks each year are also reported.

Panel A: Descriptive statistics for earnings surprises, streaks, and reversals

Panel A: Average firm characteristics by year						
Year	No of firm- quarters	ESURP	MCAP	Number of Streaks	No of Reversals	Percentage of Streaks
1991	1101	0.388	11317	620	481	0.56
1992	1019	0.454	10926	473	546	0.46
1993	1071	0.292	11364	578	493	0.54
1994	1130	0.282	11319	618	512	0.55
1995	1251	0.308	12484	668	583	0.53
1996	1237	0.281	11031	638	599	0.52
1997	1314	0.31	10178	775	539	0.59
1998	1341	0.37	9465	738	603	0.55
1999	1381	0.392	9302	697	684	0.50
2000	1378	0.4	9582	656	722	0.48
2001	1416	0.401	9986	610	806	0.43
2002	1447	0.363	10638	707	740	0.49
2003	1436	0.335	10090	631	805	0.44
2004	1412	0.357	10058	710	702	0.50
2005	1125	0.354	10765	649	476	0.58
2006	291	0.376	12554	159	132	0.55

Panel B summarises some of the firm characteristics of my S&P500 companies for the streaks and reversals of quarterly earnings surprises. The characteristics include accumulated returns from months t-11 to t-1 (MRET), analyst coverage (ACOV) is the number of analysts following the company, company age (AGE) is the number of years since the company was added to the S&P500 index, Stock volatility (SVOL) is the standard deviation of weekly market excess returns over the year ending at the end of month t, and cash-flow volatility (CVOL) is the standard deviation of cash-flow from operations in the last five years (with a minimum of three years). *, **, *** represents the associated statistical significance at 10%, 5%, and 1% respectively of the difference in average company characteristics between streaks and reversals in quarterly earnings surprises.

Panel B: Average firm characteristics by streaks and reversals

	ESURP	MCAP	MRET	ACOV	AGE	SVOL	CVOL
Streaks	0.377	10872	0.129	5.684	8.438	0.053	0.0135
Reversals	0.325	10092	0.119	5.885	8.368	0.048	0.0137
Difference	0.052***	780***	0.01***	-0.201***	0.070***	0.005***	-0.0002***

Panel C: Descriptive statistics for the sample

Panel C shows the descriptive statistics of the sample and Panel D the correlation matrix of all the variables used in analysis in this chapter. The statistics include the number of observations of each of the variables, average value, standard deviation, minimum, first quartile, median, third quartile, and maximum value respectively. The variables presented are the stocks' three-day buy-and-hold Fama-French three-factor model adjusted returns (BHAR) around the earnings announcement date, CONSISTENCY is the streaks and reversals of quarterly earnings surprises in my sample, Stock volatility (SVOL) is the standard deviation of weekly market excess returns over the year ending at the end of the most recent month, and cash-flow volatility (CVOL) is the standard deviation of cash-flow from operations in the last five years (with a minimum of three years), MRET is the accumulated returns from months t-11 to t-1, analyst coverage (ACOV) is the number of analysts following the company, company age (AGE) is the number of years since the company was added to the S&P500 index, analysts' forecast dispersion (AFORD) is the standard deviation of consensus analyst forecasts in the most current month scaled by prior year-end stock price, Firm size (MCAP) is the market capitalisation (in millions of dollars) at the end of the most current month. ESURP is the quarterly earnings surprise calculated as the I/B/E/S actual quarterly earnings minus the most recent mean consensus analysts' earnings forecast scaled by prior year end stock price. The sample includes all the S&P500 constituent companies from January 1991 to December 2006.

Variable	No. of Obs.	Mean	Std. Dev.	Min.	Q1	Median	Q3	Max.
CONSISTENCY	18249	3.418	6.5	-12	-2	3	10	12
BHAR	18248	0.02%	0.71%	-14.08%	-0.24%	0.01%	0.30%	9.41%
CVOL	18249	0.013	0.26	0	0.001	0.005	0.015	0.681
SVOL	1818	0.05	0.109	0.009	0.026	0.037	0.054	4.206
AFORD	18156	0.026	0.053	0	0.01	0.01	0.03	1.67
ACOV	18249	5.78	6.829	0	1	3	9	44
AGE	18203	8.404	4.491	1	5	8	12	20
MCAP	18093	10490.7	22477.66	2.40	1561.78	4302.83	9747.65	499070
MRET	18249	0.124	0.366	-2.498	0	0.045	0.253	3.781
ESURP	18248	0.351	0.929	-10	-0.0001	0.043	0.861	10.25

Panel D: The Pearson correlation coefficient is above the diagonal and the Spearman correlation coefficient is below

	CONSISTENCY	BHAR	ESURP	MCAP	SVOL	AFORD	ACOV	MRET	CVOL	AGE
CONSISTENCY	1	0.1262	-0.0152	0.0229	0.0136	0.0066	-0.0266	-0.0052	-0.0006	0.0554
BHAR	0.1213	1	0.0106	-0.0036	-0.0598	-0.0029	-0.0485	-0.0113	-0.0088	0.0555
ESURP	0.0292	0.0939	1	0.022	-0.0266	-0.0016	-0.017	0.022	0.0043	0.2822
MCAP	-0.0179	-0.0287	0.0252	1	-0.0778	-0.0039	0.0365	-0.0067	-0.0053	0.0229
SVOL	0.0324	-0.0844	0.0003	0.1245	1	0.0008	0.0029	0.0175	0.0128	0.001
AFORD	-0.0057	0.0013	0.0181	0.083	0.1557	1	-0.0095	0.01	0.0294	-0.0002
ACOV	-0.0027	-0.0504	0.0163	0.0087	-0.0275	-0.0132	1	-0.0059	0.0256	0.0272
MRET	0.01	-0.0221	0.0402	-0.0214	-0.0076	0.0091	0.0312	1	-0.0405	0.0015
CVOL	0.0213	0.0012	0.0011	0.0334	0.0088	0.0235	0.0729	0.0169	1	-0.006
AGE	0.0318	0.0552	0.646	0.0158	0.0441	0.0056	0.0171	-0.0194	0.0046	1

Table 5.2: Summary statistics for streaks and reversals in quarterly earnings surprises

Table 5.2 reports the frequency of streaks and reversals in my S&P500 sample during the sample period from January 1991 to December 2006. In panel A, companies are sorted into positive and negative ESURP based on the sign of ESURP in the most recent quarter. The number of streaks of various lengths, total negative and positive streaks and reversals are then observed and reported. In panel B, companies are sorted into different quintiles based on their most recent ESURP. A streak of quarterly earnings surprises occurs when at least the two most recent earnings surprises of my sample company are of the same sign (i.e. a continuation of quarterly earnings rises or falls). A temporary reversal of earnings surprise occurs when a streak is terminated. ESURP is classified as negative if it is less than zero and positive if it is greater than zero.

Number of observations by streak and reversal of earnings surprises										
Streak length	Panel A: ESURP sign				Panel B: ESURP quintile					
	Negative	Positive	% Negative	% Positive	Smallest	2	3	4	Largest	
2	1296	1916	7.2	10.5	676	644	636	666	590	
3	657	1186	3.6	6.5	388	338	453	335	329	
4	328	803	1.8	4.4	160	205	281	168	317	
5	219	547	1.2	3	119	93	140	122	292	
6	219	383	1.2	2.1	128	152	94	98	130	
7	55	310	0.3	1.7	47	102	51	60	105	
8	55	255	0.3	1.4	67	44	79	54	66	
9	36	182	0.2	1	34	39	68	44	33	
10	36	128	0.2	0.7	33	15	46	23	47	
11	18	109	0.1	0.6	24	28	27	31	17	
12	73	496	0.4	2.72	62	90	207	79	131	
All Streaks	2992	6315	32.15	67.85	1738	1750	2082	1680	2057	
Reversals	4289	4653	47.9	52.1	1912	1900	1584	1960	1586	

Table 5.3: Panel regressions of three-day buy-and-hold Fama-French three-factor model adjusted PEAD returns and consistency, earnings surprise streaks and reversals (reported coefficients are multiplied by 100)

This table reports the panel regressions intercepts and estimates for the three-day buy-and-hold Fama-French three-factor adjusted PEAD returns. A total of thirteen model regression test results are reported in this table. The three-day earnings announcement window starts a day prior to I/B/E/S earnings announcement date and ends a day after. The various model specifications of the following panel regressions are estimated whose dependent variable, $BHAR_{it-1,t+1}$, denotes the three-day buy-and-hold Fama-French three-factor model adjusted returns:

$$BHAR_{it-1,t+1} = \alpha + \beta_{i1}CONSIS + \beta_{i2}ESURP + \beta_{i3}CONSIS * ESURP + \beta_{i4}STR + \beta_{i5}STR * ESURP + \beta_{i6}DUMMY1 + \beta_{i7}DUMMY2 + \beta_{i8}DUMMY3 + \beta_{i9}DUMMY4 + \epsilon_{it}.$$

where $BHAR_{it-1,t+1}$ is the three-day buy-and-hold Fama-French three-factor model adjusted PEAD returns within a three-day earnings announcement window of (-1, +1), $CONSIS$ (Consistency) is the length of streaks of quarterly earnings surprises and temporary reversals of 1, 2,,,,,, 11, and 12 denoting rises or falls in quarterly earnings surprise lasting 1 quarter, 2 consecutive quarters, 3 consecutive quarters, 11 consecutive quarters, 12 consecutive quarters etc.; $ESURP$ is the magnitude of the quarterly earnings surprise in the most recent quarter normalised by prior year end stock price, $CONSIS * ESURP$ is an interaction term measuring the interaction between Consistency and $ESURP$, STR the streaks of quarterly earnings surprises is denoted as +1 for positive streaks and -1 for negative streaks (a streak of quarterly earnings surprises occurs when there are at least two earnings surprises of the same sign for two consecutive quarters), $STR * ESURP$ is an interaction term measuring the interaction between streaks and $ESURP$, $DUMMY1$ represents STR_POS (which is a dummy variable that equals 1 for positive streaks of quarterly earnings surprises and zero otherwise), $DUMMY2$ represents STR_NEG (which is a dummy variable that equals 1 for negative streaks of quarterly earnings surprises and zero otherwise), $DUMMY3$ represents $REVSL_POS$ (which is a dummy variable that equals 1 for positive reversal in quarterly earnings surprises and zero otherwise), $DUMMY4$ represents $REVSL_NEG$ (which is a dummy variable that equals 1 for negative reversal in quarterly earnings surprises and zero otherwise), and ϵ_{it} is random error. The sample includes all the S&P500 constituent companies from January 1991 to December 2006. The associated t-statistics are reported in parenthesis and ***, **, * indicates statistical significance at a 1%,5%, and 10% confidence level. The reported coefficients are multiplied by 100.

Model	Intercept	Consistency	ESURP	Streaks	Consis*ESURP	Streaks*ESURP	STR_POS	STR_NEG	REVSL_POS	REVSL_NEG	N
(1) $BHAR_{it-1,t+1}$	0.001 (0.15)	0.007 (1.79)									18249
(2)	0.008 (0.94)		-0.005 (-0.20)								18249
(3)	0.00003 (0.00)	0.018** (2.09)	0.011 (0.54)		-0.0001 (-1.58)						18249
(4)	-0.096*** (-3.65)	-0.006 (-1.24)		0.211*** (4.04)							18249
(5)	-0.084*** (-3.60)	-0.006 (-1.22)	-0.038 (-0.11)	0.20*** (4.03)							18249
(6)	-0.092*** (-3.75)	-0.005 (-0.98)	0.031 (0.83)	0.218*** (4.10)	-0.011* (-1.76)						18249

Table 5.3 continued from the previous page

	Intercept	Consistency	ESURP	Streaks	Consis*ESURP	Streaks*ESURP	STR_POS	STR_NEG	REVSL_POS	REVSL_NEG	N
(7)	-0.090*** (-3.72)	-0.005 (-1.12)	0.04 (0.85)	0.307*** (4.11)		-0.071 (-1.10)					18249
(8)	-0.045*** (-2.61)	-0.01 (-1.94)	-0.0005 (-0.02)				0.250*** (3.34)				18249
(9)	-0.033 (-1.55)	0.01*** (2.63)	-0.012 (-0.42)					-0.109* (-1.90)			18249
(10)	0.041*** (2.67)	0.004 (1.05)	-0.004 (-0.15)						-0.180*** (-3.06)		18249
(11)	0.026 (1.20)	0.003 (0.62)	-0.011 (-0.35)							-0.083 (-1.30)	18249
(12)	-0.091*** (-3.54)	-0.006 (-0.84)	0.041 (0.85)			-0.075 (-1.09)	0.290*** (3.58)	-0.177** (-2.33)			18249
(13)	0.107*** (3.69)	-0.004 (-0.84)	0.046 (0.93)			-0.084 (-1.18)			-0.208*** (-3.96)	-0.122** (-2.59)	18249

Table 5.4: Panel regressions of the three-day buy-and-hold Fama-French three-factor model adjusted post-earnings announcement returns and different streak lengths and signs.

This table shows the regression estimates of the three-day buy-and-hold Fama-French three-factor model adjusted PEAD returns on positive and negative streaks of various lengths. Panel regression results are reported in panels A and B while pooled OLS regression results are reported in panels C and D. A total of twelve regression models are estimated here. The regression model is:

$$BHAR_{it-1,t+1} = \alpha + \beta_{i1}CONSIS + \beta_{i2}ESURP + \beta_{i3}CONSIS * ESURP + \beta_{i4}DUMMY + \epsilon_{it}.$$

where $BHAR_{it-1,t+1}$ is the three-day buy-and-hold Fama-French three-factor model adjusted PEAD returns with a three-day earnings announcement window of (-1, +1), $CONSIS$ (Consistency) is the length of streaks of quarterly earnings surprises and temporary reversals of 1, 2,,,,,,, 11, and 12 denoting rises or falls in quarterly earnings surprises lasting 1 quarter, 2 consecutive quarters, 3 consecutive quarters, 11 consecutive quarters, 12 consecutive quarters etc.; $ESURP$ is the magnitude of the quarterly earnings surprise normalised by prior year end stock price in the most recent quarter, $CONSIS * ESURP$ is an interaction term measuring the interaction between Consistency and $ESURP$, $DUMMY$ variable represents either STR_POS_2to4 , STR_POS_5to8 , STR_POS_9to12 , STR_NEG_2to4 , STR_NEG_5to8 or STR_NEG_9to12 . STR_POS_2to4 is a dummy variable denoted as one for positive streaks of between 2 and 4 quarters and zero otherwise, STR_NEG_2to4 is a dummy variable denoted as 1 for negative streaks of between 2 and 4 quarters and zero otherwise, STR_POS_5to8 is a dummy variable denoted as 1 for positive streaks of between 5 and 8 quarters and zero otherwise, STR_NEG_5to8 is a dummy variable denoted as 1 for negative streaks of between 5 and 8 quarters and zero otherwise, STR_POS_9to12 is a dummy variable denoted as 1 for positive streaks of between 9 and 12 quarters and zero otherwise, and STR_NEG_9to12 is a dummy variable denoted as 1 for negative streaks of between 9 and 12 quarters and zero otherwise, and ϵ_{it} is random error. The sample includes all the S&P500 constituent stocks from January 1991 to December 2006. The t-statistics are reported in parenthesis and ***, **, * indicates statistical significance at a 1%, 5%, and 10% confidence level. The reported coefficients are multiplied by 100. In the OLS regressions, standard errors are robust to heteroskedasticity correction following a Huber-White robust estimation approach.

Panel A: Panel regressions of three-day buy-and-hold PEAD returns adjusted by the Fama-French three-factor model on different lengths of positive streaks (reported coefficients are multiplied by 100)

	Intercept	Consistency	ESURP	Consis*ESURP	Streak Length	N	F
STR_POS_2to4	0.011*** (62.09)	-0.0003*** (-4.30)	0.0007 (1.41)	-0.0001 (-1.05)	0.023*** (7.72)	18203	53.24(0.00)
STR_POS_5to8	0.024*** (95.2)	-0.0006*** (-7.94)	0.001*** (2.03)	-0.00001 (-0.14)	0.011*** (3.65)	18203	38.38(0.00)
STR_POS_9to12	0.029*** (115.9)	-0.0007*** (-10.10)	0.001 (1.87)	-0.00001 (-0.06)	0.004 (0.76)	18203	34.27(0.00)

Panel B: Panel regressions of three-day buy-and-hold PEAD returns adjusted by the Fama-French three-factor model on different lengths of negative streaks (reported coefficients are multiplied by 100)

	Intercept	Consistency	ESURP	Consis*ESURP	Streak Length	N	F
STR_NEG_2to4	0.02*** (99.8)	-0.0007*** (-9.95)	0.001 (1.96)	-0.0002 (-0.27)	-0.001*** (-2.24)	18203	35.7(0.00)
STR_NEG_5to8	0.02*** (123.9)	-0.0006*** (-8.07)	0.001*** (2.00)	-0.00001 (-0.18)	-0.003*** (-3.89)	18203	38.95(0.00)
STR_NEG_9to12	0.02*** (129.9)	-0.001*** (-13.21)	0.001*** (2.38)	-0.0001 (-1.27)	0.009*** (6.76)	18203	48.79(0.00)

Panel C: Pooled OLS Regression of three-day buy-and-hold post-earnings announcement returns adjusted by the Fama-French three-factor model on different lengths of positive streaks (reported coefficients are multiplied by 100) (vce(robust))

	Intercept	Consistency	ESURP	Consis*ESURP	Streak Length	N	R ²	F
STR_POS_2to4	0.02*** (288.0)	-0.0001*** (-10.25)	0.0003*** (3.07)	0.0001*** (2.11)	0.001*** (2.95)	18203	0.0092	41.65(0.00)
STR_POS_5to8	0.02*** (312.6)	-0.0001*** (-11.06)	0.0003*** (3.03)	0.0001*** (2.05)	0.001 (1.58)	18203	0.0089	39.66(0.00)
STR_POS_9to12	0.02*** (318.92)	-0.0002*** (-11.65)	0.0003*** (3.05)	0.0001*** (2.09)	0.00005 (0.08)	18203	0.0087	39.29(0.00)

Panel D: Pooled OLS regression of three-day buy-and-hold PEAD returns adjusted by the Fama-French three-factor model on different lengths of negative streaks (returns are multiplied by 100) (vce(robust))

	Intercept	Consistency	ESURP	Consis*ESURP	Streak Length	N	R²	F
STR_NEG_2to4	0.021*** (296.1)	-0.0002*** (-11.46)	0.0003*** (3.11)	0.0001*** (2.05)	-0.0002 (-1.92)	18203	0.0089	40.22(0.00)
STR_NEG_5to8	0.021*** (320.38)	-0.0002*** (-8.720)	0.0003*** (2.99)	0.0001*** (2.20)	-0.001*** (-5.99)	18203	0.0089	47.34(0.00)
STR_NEG_9to12	0.02*** (323.3)	-0.0002*** (-13.79)	0.0003*** (3.08)	0.0001*** (2.07)	0.003*** (7.35)	18203	0.01115	50.22(0.00)

Table 5.5: One-way sort of the three-day buy-and-hold Fama-French three-factor model adjusted PEAD returns by information uncertainty proxies and cumulative past stock return (reported coefficients are multiplied by 100)

The table reports three-day buy-and-hold Fama-French three-factor model adjusted PEAD returns sorted by each information uncertainty proxy and the past 11-month returns. In table 5.5, each quarter I sort stocks into five deciles based on each of the information uncertainty proxies in the most recent quarter. In the last column of table 5.5, I sort stocks into five deciles based on the past 11-month stock returns to verify the existence of momentum in my sample stock returns. Stock volatility (SVOL) is the standard deviation of weekly market excess returns over the year ending at the end of month t, and cash-flow volatility (CVOL) is the standard deviation of cash-flow from operations in the last five years (with a minimum of three years of data), MRET is the accumulated returns from months t-11 to t-1, analyst coverage (ACOV) is the number of analysts following the company, company age (AGE) is the number of years since the company was added to the S&P500 index, analysts' forecast dispersion (AFORD) is the standard deviation of consensus analyst forecasts in the most current month scaled by prior year-end stock price, Firm size (MCAP) is the market capitalisation (in millions of dollars) at the end of the most current month. 1/MV, 1/AGE, and 1/ACOV are the reciprocals of MV, AGE, and ACOV respectively. The sample includes all the S&P500 constituent stocks from January 1991 to December 2006. The associated t-statistics are reported in parenthesis and ***, **, * indicates statistical significance at a 1%, 5%, and 10% confidence level. The reported coefficients are multiplied by 100.

	Sorted by 1/MV	Sorted by 1/AGE	Sorted by 1/ACOV	Sorted by AFORD	Sorted by SVOL	Sorted by CVOL	sorted by MRET
Q1(Low)	0.034	0.014	0.021	0.015	0.032	0.032	-0.046
Q2	0.021	0.020	0.003	0.030	0.045	-0.001	0.012
Q3	0.013	0.028	0.014	0.035	0.001	0.031	0.024
Q4	0.030	0.037	0.023	-0.006	0.017	0.016	0.050
Q5 (High)	0.010	0.001	0.010	0.012	0.007	0.025	0.080
Difference(Q5-Q1)	-0.024	-0.013	-0.011	-0.003	-0.025	-0.007	0.126***
	(-1.43)	(-0.91)	(-0.55)	(-0.34)	(-1.55)	(-0.48)	(6.66)

Table 5.6: A two-way sort of the three-day buy-and-hold Fama-French three-factor model adjusted PEAD returns by information uncertainty proxies and streaks of quarterly earnings surprises (reported coefficients are multiplied by 100)

This table reports the three-day buy-and-hold Fama-French three-factor adjusted PEAD returns sorted by information uncertainty proxy and streaks of quarterly earnings surprises. First, I categorise the stocks into negative and positive streaks based on the sign of their streaks in the most current quarter. Each category is subsequently sorted by stocks into portfolios of high and low levels information uncertainty based on the median of each of the information uncertainty proxies. An information uncertainty level below the median is categorised as low, whereas an information uncertainty level above the median is categorised as high. Stock volatility (SVOL) is the standard deviation of weekly market excess returns over the year ending at the end of month t, and cash-flow volatility (CVOL) is the standard deviation of cash-flow from operations in the last five years (with a minimum of three years data), analyst coverage (ACOV) is the number of analysts following the company, company age (AGE) is the number of years since the company was added to the S&P500 index, analysts' forecast dispersion (AFORD) is the standard deviation of consensus analyst forecasts in the most current month scaled by prior year-end stock price, Firm size (MCAP) is the market capitalisation (in millions of dollars) at the end of the most current month. 1/MV, 1/AGE, and 1/ACOV are the reciprocals of MV, AGE, and ACOV respectively. **Pos_STR** is composed of positive quarterly earnings surprises of various lengths while **Neg_STR** is composed of negative quarterly earnings surprises of various lengths, **HML** represents a portfolio return of high information uncertainty portfolio minus low information uncertainty portfolio. The sample includes all the S&P500 constituent stocks from January 1991 to December 2006. The associated t-statistics are reported in parenthesis and ***, **, * indicates statistical significance at a 1%, 5%, and 10% confidence level. The reported coefficients are multiplied by 100.

	Sorted by 1/MV				Sorted by 1/AGE				Sorted by 1/ACOV		
	High IU	Low IU	HML		High IU	Low IU	HML		High IU	Low IU	HML
Pos_STR	0.038*** (3.45)	0.0008 (0.06)	0.037** (2.15)	Pos_STR	0.040*** (3.65)	0.005 (0.24)	0.037** (2.24)	Pos_STR	0.027** (2.37)	0.009 (0.62)	0.021 (1.45)
Neg_STR	0.035** (2.12)	0.035* (1.65)	0.0007 (0.03)	Neg_STR	0.005 (0.24)	0.067*** (4.16)	-0.058** (-2.23)	Neg_STR	0.039** (2.55)	0.030 (1.25)	0.016 (0.72)
Pos_STR- Neg_STR	0.004 (0.18)	-0.058** (-1.99)		Pos_STR- Neg_STR	0.027 (1.46)	-0.058** (-2.21)		Pos_STR- Neg_STR	0.009 (0.71)	-0.006 (-0.34)	

Table 5.6 continued from the previous page

	Sorted by SVOL			Sorted by CVOL			Sorted by AFORD				
	High IU	Low IU	HML	High IU	Low IU	HML	High IU	Low IU	HML		
Pos_STR	0.012 (0.91)	0.031** (2.45)	-0.017 (-1.02)	Pos_STR	0.031** (2.43)	0.008 (0.64)	0.029* (1.65)	Pos_STR	0.021 (1.57)	0.018 (1.60)	0.004 (0.23)
Neg_STR	0.036* (1.69)	0.035** (2.03)	-0.001 (-0.04)	Neg_STR	0.041** (2.32)	0.030 (1.46)	0.009 (0.34)	Neg_STR	0.013 (0.58)	0.056*** (3.32)	0.044* (-1.74)
Pos_STR- Neg_STR	-0.005 (-0.31)	0.012 (0.77)		Pos_STR- Neg_STR	0.012 (0.84)	-0.007 (-0.44)		Pos_STR- Neg_STR	0.015 (0.81)	-0.005 (-0.35)	

Table 5.7: A two-way sort of the three-day buy-and-hold Fama-French three-factor model adjusted PEAD returns by information uncertainty proxies and streaks of quarterly earnings surprises of various lengths (reported coefficients are multiplied by 100)

The table reports the three-day buy-and-hold Fama-French three-factor adjusted PEAD returns sorted by information uncertainty proxy and lengthening streaks of quarterly earnings surprises. First, I categorise the stocks into negative and positive streaks based on the sign and length of their streaks in the most current quarter. Each category is subsequently sorted by stocks into portfolios of high and low levels information uncertainty based on the median of each of the information uncertainty proxies. Panels A, B, and C show the returns when quarterly earnings surprises streaks of between two to four, five to eight, and nine to twelve consecutive quarters are employed respectively. Stock volatility (SVOL) is the standard deviation of weekly market excess returns over the year ending at the end of month t , and cash-flow volatility (CVOL) is the standard deviation of cash-flow from operations in the last five years (with a minimum of three years), analyst coverage (ACOV) is the number of analysts following the company, company age (AGE) is the number of years since the company was added to the S&P500 index, analysts' forecast dispersion (AFORD) is the standard deviation of consensus analyst forecasts in the most current month scaled by prior year-end stock price, Firm size (MCAP) is the market capitalisation (in millions of dollars) at the end of the most current month. $1/MV$, $1/AGE$, and $1/ACOV$ are the reciprocals of MV , AGE , and $ACOV$ respectively. **Pos_STR** represents lengthening streaks of positive quarterly earnings surprises while **Neg_STR** represents lengthening streaks of negative quarterly earnings surprises; **HML** represents a portfolio return of high information uncertainty portfolio minus low information uncertainty portfolio. The sample includes all the S&P500 constituent stocks from January 1991 to December 2006. The associated t-statistics are reported in parenthesis and ***, **, * indicates statistical significance at a 1%, 5%, and 10% confidence level. The reported coefficients are multiplied by 100.

Panel A: Returns by information uncertainty proxy and quarterly earnings surprises streaks of between 2 and 4 quarters in length (reported coefficients are multiplied by 100)

	Sorted by 1/MV			Sorted by 1/AGE			Sorted by 1/ACOV				
	High IU	Low IU	HML	High IU	Low IU	HML	High IU	Low IU	HML		
Pos_STR	0.049*** (3.41)	-0.012 (-0.65)	0.061*** (2.58)	Pos_STR	0.036*** (2.61)	0.004 (0.24)	0.034 (1.37)	Pos_STR	0.015 (0.97)	0.024 (1.25)	-0.026 (-0.98)
Neg_STR	0.037* (1.82)	0.033 (1.28)	0.004 (0.12)	Neg_STR	-0.005 (-0.19)	0.075*** (4.19)	-0.08** (-2.29)	Neg_STR	0.037*** (2.09)	0.032 (1.05)	0.015 (0.51)
Pos_STR-Neg_STR	0.028 (1.02)	-0.031 (-0.83)		Pos_STR-Neg_STR	0.037 (1.62)	-0.033 (-1.63)		Pos_STR-Neg_STR	-0.007 (-0.36)	0.004 (0.16)	

Table 5.7 continued from the previous page

	Sorted by SVOLNEW			Sorted by CVOLNEW			Sorted by AFORD				
	High IU	Low IU	HML	High IU	Low IU	HML	High IU	Low IU	HML		
Pos_STR	0.004 (0.20)	0.033** (2.25)	-0.029 -1.24	Pos_STR	0.020 (1.14)	0.017 (1.06)	0.004 (0.18)	Pos_STR	0.013 (0.73)	0.015 (1.11)	-0.013 (-0.65)
Neg_STR	0.037 (1.44)	0.033 (1.61)	0.002 0.07	Neg_STR	0.033 (1.55)	0.037 (1.50)	-0.006 (-0.20)	Neg_STR	0.004 (0.15)	0.058*** (3.11)	-0.056 (-1.92)
Pos_STR-Neg_STR	-0.017 (-0.73)	0.013 (0.68)		Pos_STR-Neg_STR	0.001 (0.07)	-0.006 (-0.27)		Pos_STR-Neg_STR	0.011 (0.42)	-0.011 (-0.58)	

Panel B: Returns by information uncertainty proxy and quarterly earnings surprises streaks of between 5 and 8 quarters in length (reported coefficients are multiplied by 100)

	Sorted by 1/MV			Sorted by 1/AGE			Sorted by 1/ACOV				
	High IU	Low IU	HML	High IU	Low IU	HML	High IU	Low IU	HML		
Pos_STR	0.046*** (3.71)	-0.003 (-0.20)	0.048** (2.43)	Pos_STR	0.047*** (3.94)	0.001 (0.08)	0.050*** (2.85)	Pos_STR	0.029** (2.31)	0.009 (0.53)	0.024 (1.45)
Neg_STR	0.035** (2.0)	0.035 (1.60)	-0.0005 (-0.02)	Neg_STR	0.006 (0.27)	0.067*** (3.97)	-0.056* (-1.91)	Neg_STR	0.041*** (2.58)	0.028 (1.08)	0.021 (0.84)
Pos_STR-Neg_STR	0.027* (1.76)	-0.022 (-1.12)		Pos_STR-Neg_STR	0.043* (1.86)	-0.029* (-1.71)		Pos_STR-Neg_STR	-0.007 (-0.26)	-0.033 (-1.01)	
	Sorted by SVOLNEW			Sorted by CVOLNEW			Sorted by AFORD				
	High IU	Low IU	HML	High IU	Low IU	HML	High IU	Low IU	HML		
Pos_STR	0.012 (0.87)	0.031** (2.21)	-0.016 (-0.82)	Pos_STR	0.035** (2.37)	0.007 (0.55)	0.028 (1.41)	Pos_STR	0.023 (1.53)	0.020 (1.49)	(0.015) (0.69)
Neg_STR	0.034 (1.56)	0.036 (2.01)	-0.003 (-0.12)	Neg_STR	0.041 (2.25)	0.029 (1.38)	0.010 (0.36)	Neg_STR	0.007 (0.31)	0.056*** (3.39)	-0.029 (-0.94)
Pos_STR-Neg_STR	-0.005 (-0.25)	0.01 (0.60)		Pos_STR-Neg_STR	0.013 (0.77)	-0.009 (-0.49)		Pos_STR-Neg_STR	0.019 (0.95)	-0.009 (-0.61)	

Panel C: Returns by Information Uncertainty proxy and quarterly earnings surprises streaks of between 9 and 12 quarters in length (reported coefficients are multiplied by 100)

	Sorted by 1/MV			Sorted by 1/AGE			Sorted by 1/ACOV				
	High IU	Low IU	HML	High IU	Low IU	HML	High IU	Low IU	HML		
Pos_STR	0.003	0.027	-0.025	Pos_STR	-0.005	0.025	-0.028	Pos_STR	0.015	0.012	0.007
	(0.11)	(0.97)	(-0.61)		(-0.19)	(0.95)	(-0.89)		(0.59)	(0.38)	(0.23)
Neg_STR	0.044	0.028	-0.002	Neg_STR	-0.014	0.064	-0.072	Neg_STR	0.007	0.066	-0.059
	(0.86)	(0.39)	(-0.02)		(-0.18)	(1.29)	(-1.04)		(0.11)	(1.13)	(-0.72)
Pos_STR-Neg_STR	-0.005	0.021		Pos_STR-Neg_STR	-0.003	0.013		Pos_STR-Neg_STR	0.014	-0.004	
	(-0.17)	(0.71)			(-0.09)	(0.47)			(0.52)	(-0.11)	

	Sorted by SVOLNEW			Sorted by CVOLNEW			Sorted by AFORD				
	High IU	Low IU	HML	High IU	Low IU	HML	High IU	Low IU	HML		
Pos_STR	0.003	0.022	-0.019	Pos_STR	0.015	0.012	0.006	Pos_STR	0.012	0.015	-0.008
	(0.11)	(0.82)	(-0.54)		(0.56)	(0.41)	(0.16)		(0.38)	(0.59)	(-0.24)
Neg_STR	0.052	0.018	0.036	Neg_STR	0.036	0.038	-0.005	Neg_STR	-0.052	0.090	-0.12
	(0.88)	(0.30)	(0.49)		(0.63)	(0.60)	(-0.07)		(-0.69)	(1.75)	(-1.80)
Pos_STR-Neg_STR	-0.008	0.019		Pos_STR-Neg_STR	0.010	0.003		Pos_STR-Neg_STR	0.021	-0.001	
	(-0.26)	(0.67)			(0.35)	(0.12)			(0.63)	(-0.04)	

Table 5.8: A one-way sort of the three-day buy-and-hold Fama-French three-factor model adjusted PEAD returns sorted by analyst forecast revisions (reported coefficients are multiplied by 100)

This table reports the three-day buy-and-hold Fama-French three-factor model adjusted PEAD returns sorted by analyst forecast revision. First the stocks are sorted into three different groups based on their most current analyst forecast revision. The analyst forecast revision is the average of all the revisions reported by individual analysts following the company in the most current forecast. Analysts' revisions are categorised as good news (upward revision), no news (no change in revision), and bad news (downward revision). The sample includes all the S&P500 constituent stocks from January 1991 to December 2006. The associated t-statistics are reported in parenthesis and ***, **, * indicates statistical significance at a 1%, 5%, and 10% confidence level. The reported coefficients are multiplied by 100.

	Sample	BHAR _{t-1, t+1}
Bad News (AFORR _t < 0)	21.24%	0.001 (0.16)
No News (AFORR _t = 0)	53.05%	0.010 (1.07)
Good news (AFORR _t > 0)	25.71%	0.030*** (4.45)
Good news - Bad news		0.029*** (3.90)

Table 5.9: The three-day buy-and-hold Fama-French three-factor model adjusted PEAD returns by information uncertainty Proxy and analyst forecast revisions (reported coefficients are multiplied by 100)

This table reports the three-day buy-and-hold Fama-French three-factor model adjusted PEAD returns sorted by analyst forecast revision and information uncertainty proxy. First, I categorise the stocks into good news, no news, and bad news based on their most current analyst forecast revision. In each category stocks are subsequently sorted into portfolios of high and low levels of information uncertainty based on the median of each of the information uncertainty proxies. Stock volatility (SVOL) is the standard deviation of weekly market excess returns over the year ending at the end of month t, and cash-flow volatility (CVOL) is the standard deviation of cash-flow from operations in the last five years (with a minimum of three years), analyst coverage (ACOV) is the number of analysts following the company, company age (AGE) is the number of years since the company was added to the S&P500 index, analysts' forecast dispersion (AFORD) is the standard deviation of consensus analyst forecasts in the most current month scaled by prior year-end stock price, Firm size (MCAP) is the market capitalisation (in millions of dollars) at the end of the most current month. 1/MV, 1/AGE, and 1/ACOV are the reciprocals of MV, AGE, and ACOV respectively. **HML** represents a portfolio return of high information uncertainty portfolio minus low information uncertainty portfolio. The sample includes all the S&P500 constituent stocks from January 1991 to December 2006. The associated t-statistics are reported in parenthesis and ***, **, * indicates statistical significance at a 1%, 5%, and 10% confidence level. The reported coefficients are multiplied by 100.

	Sorted by 1/MV			Sorted by 1/AGE			Sorted by 1/ACOV				
	High IU	Low IU	HML	High IU	Low IU	HML	High IU	Low IU	HML		
Good News (AFORRt>0)	0.058*** (2.66)	0.009 (0.23)	0.062** (2.18)	Good News (AFORRt>0)	0.028 (1.52)	0.026 (1.23)	0.006 (0.21)	Good News (AFORRt>0)	0.034* (1.80)	0.017 (1.02)	0.021 0.93
Bad News (AFORRt<0)	0.019 (0.95)	-0.013 (-0.50)	0.031 (0.98)	Bad News (AFORRt<0)	0.010 (0.50)	-0.004 (-0.17)	0.014 (0.43)	Bad News (AFORRt<0)	-0.002 (-0.13)	0.011 (0.48)	-0.010 (-0.35)
Good News - Bad News	0.046** (2.18)	-0.090 (1.22)		Good News - Bad News	0.038 (1.15)	-0.018 (-0.40)		Good News - Bad News	0.043 (1.62)	0.008 (0.28)	

Table 5.9 continued from the previous page

	Sorted by AFORD				Sorted by SVOL				Sorted by CVOL		
	High IU	Low IU	HML		High IU	Low IU	HML		High IU	Low IU	HML
Good News (AFORRt>0)	0.028*	0.024	0.009	Good News (AFORRt>0)	0.034*	0.020	0.013	Good News (AFORRt>0)	0.058***	-0.004	0.062**
	(1.75)	(1.04)	(0.39)		(1.78)	(1.0)	(0.47)		(3.25)	(-0.19)	(2.23)
Bad News (AFORRt<0)	-0.015	0.016	-0.028	Bad News (AFORRt<0)	-0.010	0.016	-0.027	Bad News (AFORRt<0)	0.036*	-0.032	0.069**
	(-0.62)	(0.78)	(-1.01)		(-0.42)	(0.76)	(-0.81)		(1.81)	(-1.25)	(2.06)
Good News - Bad News	0.037	0.012		Good News - Bad News	0.059	-0.036		Good News - Bad News	0.11	-0.106	
	(1.20)	(0.43)			(1.40)	(-0.59)			(1.16)	(-0.78)	

Figure 5.1: The distribution frequency of streaks of quarterly earnings rises, falls and temporary reversals in the streaks of earnings surprises.

Figure 5.1 below shows the distribution of the frequency of quarterly earnings falls, rises, and temporary reversals in streaks of earnings surprises. The distribution evidently shows that there are far more consecutive quarterly earnings rises than consecutive quarterly earnings falls in my S&P500 sample data. The figure shows a distribution consisting of 51% positive and negative streaks (continuations) and 49% temporary positive and negative reversals in earnings surprises continuations. A streak in an earnings surprise sequence occurs when there is a rise or fall in quarterly earnings outcomes for two consecutive quarters or more. However, a temporary reversal in earnings surprise continuation occurs when a growing streak is terminated by an earnings surprise of the opposing sign in the most recent quarter.

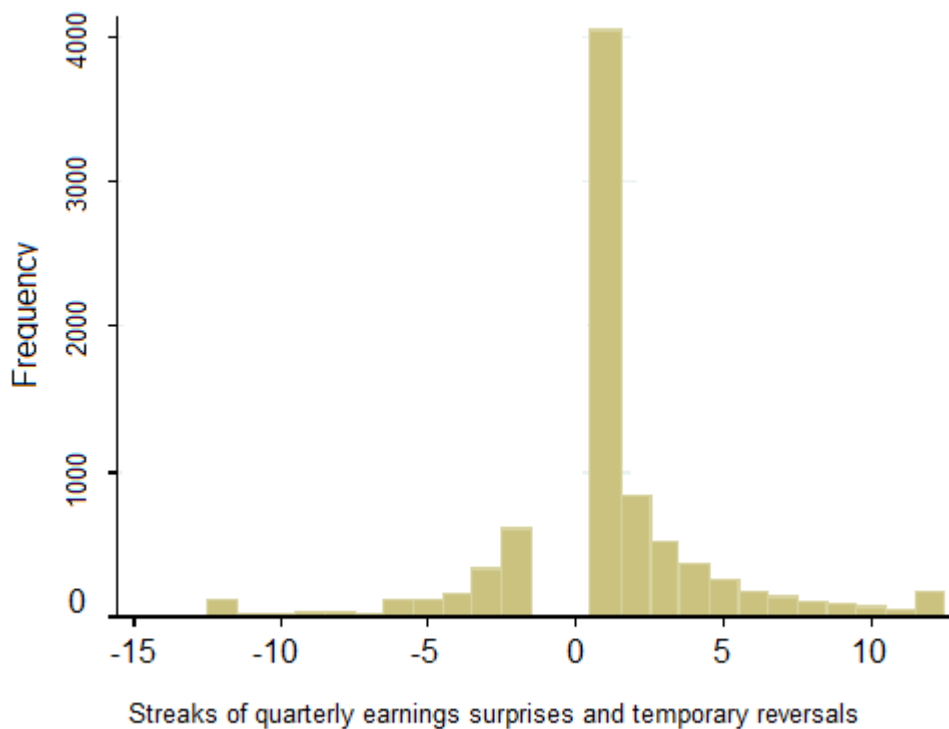
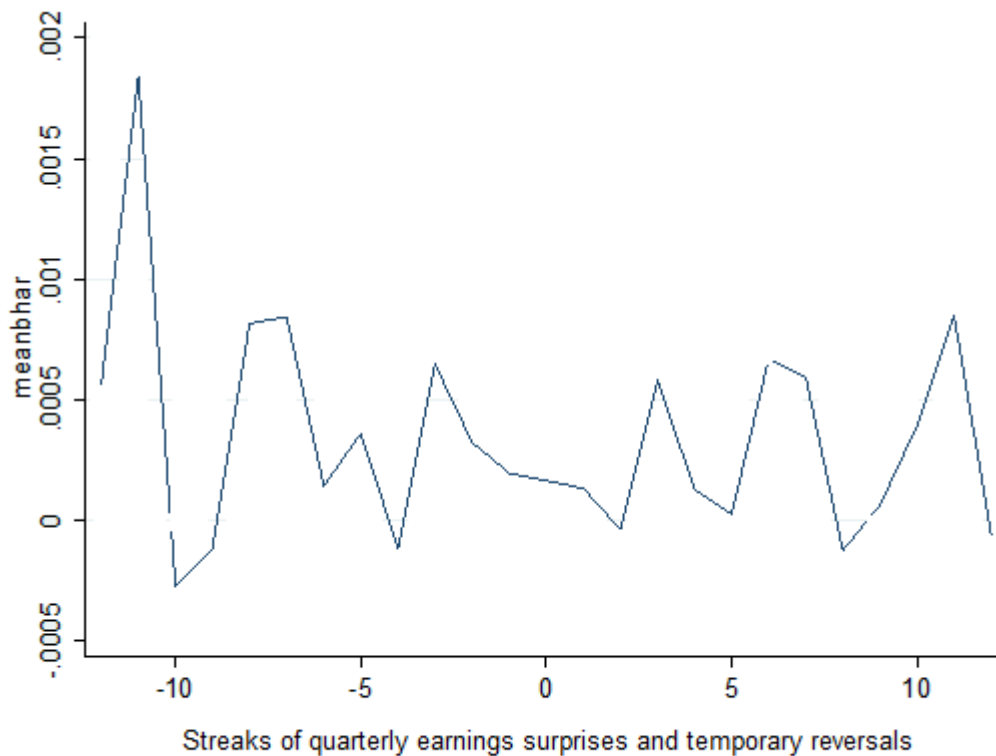


Figure 5.2: The mean of three-day buy-and-hold Fama-French three-factor model adjusted PEAD returns traced by streaks of earnings surprises over a period of twelve quarters.

The figure plots the most recent streaks of quarterly earnings surprises and temporary reversals in streaks against the mean of the three-day buy-and-hold Fama-French three-factor adjusted PEAD returns. The variable (meanbhar) is the mean of the three-day buy-and-hold Fama-French three-factor adjusted returns grouped by streaks of quarterly earnings surprises of various lengths and by temporary positive and negative reversals in the most current quarter. A temporary reversal in quarterly earnings surprises occurs when a growing streak of either positive or negative earnings surprises is terminated at the most recent quarter.



Chapter Six

Conclusion, limitations, and further research work

6.1 Introduction

In standard finance theory, security prices are assumed to fully reflect all of the available information (including the fundamental associated risks), and investors are fully Bayesian and are rational. According to the standard finance model, a rational representative investor is one who applies Bayes' rule to make optimal investment decisions. This rational investor should also conform to the model of expected utility theory and all its prescriptions for how an investor should behave, as given by von Neumann and Morgenstern (1947). However, over the years this wonderful model has failed to hold up when researchers subject it to empirical tests employing security prices and other financial data.

In view of the above, behavioural finance theory emerged to provide an alternative (or maybe complementary) paradigm to the standard finance theory. The propositions of rational expectation theory and the efficient market hypothesis do not seem to explain price behaviour in the face of some firm-related news events. Statman (1999) observes that 'market efficiency' has two meanings. The first advocates that investors cannot systematically beat the market, while the second supports that securities are rationally priced in the markets. He argues that rational prices will only reflect utilitarian characteristics of the security such as risk and do not reflect its value-expressive characteristics such as sentiment, purpose and belief. Investments like sport, faith, and politics are inherently social activities in which purpose, meaning, and expression are vital. He advocates a model of asset pricing which reflects both the utilitarian and value-expressive characteristics to address the limitations of the rational expectation models. In addition, a number of empirical studies provide evidence which runs contrary to the propositions of efficient market hypothesis positing that new information is quickly incorporated into security prices and that any form of mispricing will be arbitrated away almost instantaneously by informed traders. Lee (2001) posits that this view of market efficiency is very naïve and narrow. The author advocates for a more encompassing, broader model which will find room for noise traders who trade for liquidity or simply the excitement released by doing so. Furthermore, the presence of anomalies such as earnings momentum or drift in stock prices after earnings announcements poses a great challenge to the efficient market hypothesis. To support their argument, advocates of a behavioural finance approach argue that investors and other market participants are influenced by cognitive biases and heuristics, while at the same time

arguing that the effect of arbitrage in correcting mispricing is limited because it is risky and expensive⁴³.

This thesis seeks to contribute to the on-going debate on how best to explain the earnings-generated momentum or post-earnings announcement drift seen in stock returns after earnings announcements. There is growing interest in the study of earnings momentum for various reasons. First, there is evidence in the literature that earnings momentum-based portfolio strategies are profitable⁴⁴. Other evidence from empirical studies shows that price momentum is subsumed by the systematic component of earnings momentum in both time series and cross-sectional models⁴⁵. There is also growing interest in identifying the true innovation in quarterly earnings news (i.e. the systematic component of earnings news). Over the years, empirical behavioural finance researchers have focused on standardised unexpected earnings (SUE) and other measures of earnings surprise as the most important proxies to explain earnings momentum in stock returns. However, in more recent years, with empirical works based on the predictions of theoretical behavioural finance models such as Rabin (2002b), Rabin and Vayanos (2010), and Barberis, Shleifer, and Vishny (1998), this focus is shifting. Recent empirical works on earnings momentum are redirecting their focus to sequences of changes in earnings and streaks of earnings surprises as the true innovation (or the systematic component) in quarterly earnings news (see Loh and Warachka (2012), Forbes and Igboekwu (2013), Shanthikumar (2012)). ‘Streakiness’ in earnings is emerging as a new valuation characteristic. This recent shift has been occasioned by the predictions of the theoretical models mentioned above which show that when investors observe streaks of positive or negative earnings surprises, they are influenced by the law of small numbers (or other cognitive bias such as the gambler’s fallacy, which is one of the manifestations of the law of small numbers) to underreact to quarterly earnings news. This evidence points to the fact that quarterly earnings news in itself offers little or limited amount of information to the market, and that the real informativeness of quarterly earnings news lies in its ability to confirm or refute the continuation of a growing streak of earnings surprises of a particular sign. This confirmation, or termination, of a growing streak of earnings surprises seems to be the true force that drives earnings momentum in stock returns.

Hirshleifer (2001) posits that cognitive bias is likely to be more prevalent when the fundamental value of assets is uncertain: the scope for muddled thinking is simply wider

⁴³ See Shleifer and Summers (1990); Shleifer and Vishny (1997).

⁴⁴ See Chan *et al* (1996), Grundy and Martin (2001), Jegadeesh and Titman (2001), Rouwenhorst (1998).

⁴⁵ See Chordia and Shivakumar (2006).

when widely diverging views can be held by equally well-reasoning investors. Uncertainty reduces the degree of anticipation of announced earnings and intensifies investors' response to earnings at the announcement date, when uncertainty is partially or fully resolved. Further to the above position, information uncertainty has been identified in the existing empirical literature to have a positive relation with earnings momentum when it is conditioned on the nature of earnings news (i.e. bad or good news) (see Zhang (2006a, 2006b), Jang *et al* (2005)). By conditioning information uncertainty upon streaks of negative and positive earnings surprises to examine its impact on earnings momentum, my thesis contributes to the stream of new research in the information uncertainty literature which sheds light on the way in which the wider financial markets operate.

I show how my S&P500 sample companies' returns change with increasing 'streakiness' in quarterly earnings over a period of twelve quarters. For those companies with lengthening streaks of positive earnings surprises I ask, how does the investor respond to price when in the grip of the gambler's fallacy? Is the gambler's fallacy weaker unconditionally for longer streaks? Rabin (2002b) predicts that the gambler's fallacy is undermined by the hot-hand fallacy when investors update their beliefs after observing longer streaks of earnings surprises in a single direction. Loh and Warachka (2012) report that there is no unconditional evidence to support the position that investors update their earnings expectations after observing long streaks. However, by intuition, investors should expect extreme earnings growth paths to mean-revert in the long-term, because, as they say, "trees don't grow to the sky".

Finally, this thesis contributes to the academic literature by way of the data sample and methods employed to carry out this study. Some academics believe that illiquid or thinly traded stocks drive momentum⁴⁶; my thesis examines stocks of some of the most highly capitalised and liquid stocks not just in the United States but in the world. My work contributes to the literature in showing that the earnings momentum's pervasiveness cuts across even the most liquid stocks in the market. This thesis also shows that earnings momentum is present in both the short- and medium-term windows, counteracting the argument that momentum is a result of external noise in the market or simply poor asset return benchmarking. The implication of this is that most major funds would naturally hold these stocks and could engage in portfolio rebalancing amongst them, via high frequency trades, with almost no trading costs and minimal liquidity risks.

In the first empirical chapter of this thesis, I examine the predictive performance of two representative agent models of earnings momentum using my S&P500 sample data frame.

⁴⁶ See Bhootra (2011).

For lengthening sequences of positive and negative quarterly earnings changes over a period of a twelve-quarter horizon, I seek to establish whether these models can adequately capture the likelihood of reversion. I also examine the market's response to observed sequences of quarterly earnings changes in my sample over four-, eight-, and twelve-quarter horizons. The chapter also examines the behaviour of a quasi-Bayesian representative investor when he is under the influence of a cognitive bias known as the law of small numbers. In the second empirical chapter, I seek to establish the impact of streaks of negative or positive earnings surprises on the market response to quarterly earnings news. In that chapter, I employ a different metric to capture quarterly earnings surprises by using monthly analysts' forecasts and actual quarterly earnings, and thus an implicit analysts' forecasts error. Evidence in the literature suggests that the monthly analyst forecast is a more accurate measure of market expectations, since it is adjusted once actual quarterly earnings are announced. It embeds non-earnings information such as current market conjectures about the regulatory and technological risks the company faces⁴⁷. In a bid to validate the results of the market response to sequences of quarterly earnings changes found in chapter 4, I also examine in chapter 5 the market responses to negative and positive streaks of earnings surprises within a three-day window around the earnings announcement date. I examine the impact of information uncertainty variables on post-earnings announcement drift conditioned on the negative and positive streaks of quarterly earnings surprises. Tests for robustness are conducted in both chapters 4 and 5.

In this final chapter of the thesis, the next section summarises and discusses the main empirical findings of chapters 4 and 5. It also presents the implications of my findings and the contributions they make to our understanding of how stock markets incorporate information about quarterly earnings into equity prices. Section 6.3 reflects upon the limitations of this study and the final section discusses the possibilities for further research building on this research work.

6.2 Summary, implications of results, and contributions to literature

The failure of the efficient market and rational expectation-based models to unravel the puzzle behind anomalies prevalent in security returns has led scholars to seek an alternative theory to explain these puzzles. This led to the birth of an alternative paradigm to the standard finance theory known as behavioural finance theory. In recent decades, a number of partially integrative behavioural finance theoretical models have developed; these include those proposed by Daniel, Hirshleifer, and Subrahmanyam (1998), Barberis, Shleifer, and Vishny (1998), Hong and Stein (1999), Rabin (2002b), and Rabin and Vayanos (2010)

⁴⁷ See Givoly and Lakonishok (1979, 1984), Givoly (1985).

amongst others. Prior to these behavioural models being propounded, the majority of empirical behavioural studies were based on an ad hoc approach with no fundamental backing from theory. A sort of '*anomaly du jour*' cottage industry of empirical studies flourished. Subsequently, there has been a growing interest in empirical behavioural finance research in applying theory in order to ensure that such works have rigour and can withstand theoretical scrutiny. This growing interest in applying behavioural finance models in empirical studies is the major motivating factor behind this research work. The predictions of Barberis, Shleifer, and Vishny (1998) and the Rabin (2002b) model motivated me to investigate the response of the representative investor whose investment decision-making becomes flawed when he is under the influence of certain cognitive biases and heuristics. The cognitive biases involved in this study are the law of small numbers and the gambler's fallacy. The results of the empirical chapters seem to suggest that investors underreact to earnings news when they observe sequences or streaks of quarterly earnings changes and persistent forecast errors; these lead to the earnings momentum effect in stock returns. This underreaction is thought to be attributed to the influence of the law of small numbers and the gambler's fallacy.

The first empirical chapter (chapter 4) examines the predictive performance of the Barberis, Shleifer, and Vishny (1998) model and the Rabin (2002b) model and how their predictions fit into the quarterly earnings change distribution of my S&P500 constituent companies' sample frame. Barberis *et al's* (1998) model makes a prediction of symmetry between momentum and reversion regimes whereas the Rabin (2002b) model makes no such predictions for symmetry. In the Barberis *et al* (1998) model, the investor believes he is observing an earnings process that constantly cycles between eras of momentum and reversion despite the fact that in reality, earnings always follow a random process. What this belief shows is that in the Barberis *et al* (1998) model, the investor seems to be completely irrational: he is "always wrong but never in doubt". In other words, there is never any form of learning in the world of this type of investor. However, for the Rabin (2002b) model, the representative investor (Freddy) is just an imperfect Bayesian in the projection of earnings. This believer in the law of small numbers is at least quasi-Bayesian; however his predictions become more extreme when he observes two successive quarterly earnings increases. Rabin recognises this overinference based on successive increases in quarterly earnings as the effect of the gambler's fallacy on the investor. So the Barberis *et al* (1998) model makes more dramatic claims about investor rationality than the Rabin (2002b) model. From the results of my analysis, the distribution of the quarterly earnings changes is in fact asymmetric across streaks of positive and negative earnings outcomes. The observed distribution of quarterly earnings shows that there is more momentum in earnings than earnings reversals. The

Barberis *et al* (1998) model's prediction is quite the opposite of the results of my analysis, as the model assigns a higher probability of reversal than continuation of quarterly earnings. From the above findings, I conclude that it is most probably not wise to pool consistent quarterly earnings rises and falls into the same state, as the Barberis *et al* (1998) model seems to require. The requisite symmetry this sort of model (the BSV model) implies is not present in my sample data. This is more so because the cumulative impact of extreme quarterly earnings falls on abnormal returns is far more dramatic than that of smaller extreme consecutive quarterly earnings rises. Furthermore, consistent quarterly earnings rises are common; more than 21% of my sample derives from consistent quarterly earnings rises of twelve quarters' duration. Hence it is unlikely they will have a dramatic stock market impact. Furthermore, because of the simplicity of the distinction between trending and mean-reverting regimes in the Barberis *et al* (1998) model, and without regard to the length of each sequence that prevails, I conclude that the model is unlikely to capture true investor behaviour in the real world. My data shows that the length of sequence of earnings changes is crucial to explaining momentum in stock returns. Following the above findings, I choose the predictions of Rabin (2002b) as my preferred model for testing my hypotheses. From the above, I make a direct contribution to the literature by showing that the distribution of quarterly earnings falls and rises of my S&P500 companies does not fit the symmetrical distribution predicted by the Barberis *et al* (1998) model.

The remaining part of chapter 4 seeks to ascertain how surprised investors are by consecutive quarterly earnings changes regardless of their frequency or intensity, and consequently, what is the price impact of that? Does it matter for price continuation what the consistency, sign and intensity of quarterly earnings changes are?

The next empirical test in chapter 4 examines the impact of sequences of positive and negative quarterly earnings changes on the returns, assuming the investor is under the influence of the law of small numbers. The test examines the overinference exhibited by the quasi-Bayesian investor in the Rabin (2002b) model when he observes more than two successive quarterly earnings increases. The results show that the impact of the sequences of quarterly earnings falls and rises on abnormal returns is reversed for consecutive sequences of more than eight quarters. Therefore, the intensity and sign of quarterly earnings change sequences do matter, as their impact on returns shows. As the sequences of quarterly earnings rises continues to grow, the market seems 'less surprised' at the arrival of yet another confirming quarterly earnings news, and the market response to such news is more muted. However, companies reporting consecutive quarterly earnings falls beyond eight quarters appear to pay premia to their long-suffering investors, as returns are larger, positive, and highly statistically significant.

This finding contributes to the literature in establishing that the true innovation in quarterly earnings news lies either in the confirmation, or refutation, of a continuation in a growing trend of quarterly earnings rises or falls. The absolute change in quarterly earnings which represents the shock in quarterly earnings magnitude does not carry much information to have significant impact on my sample stock prices. Another contribution is that there appears to be a potential portfolio strategy that could be exploited by going long on stocks with sequences of quarterly earnings rises and shorting those with sequences of quarterly earnings falls. My results suggest that this portfolio strategy is profitable.

In addition, I examine the impact of sequences of quarterly earnings rises and falls in sub-periods and in the different industry sectors to ascertain whether the main results are driven by certain industry sectors, or a particular time period. The results of these tests show that the behaviour is widespread amongst all the industry sectors represented and that earnings momentum is not confined to any particular time period. This finding is inconsistent with the findings of Moskowitz and Grinblatt (1999), who argue that momentum in their sample is driven by industry sectors. While I am not certain as to why there is inconsistency between their finding and the finding of this thesis, I do note the difference between the scope and nature of their sample firms and mine. Their data sample covers a wider range of firms in terms of size (their sample includes stocks from the NYSE, AMEX, and NASDAQ), while my sample of S&P500 constituent companies represents the top end of the most capitalised and liquid companies in the United States. Following Da, Gurun, and Warachka's (2014) procedures, I also test for the impact of information discreteness on earnings momentum in my sample. The results suggest that information discreteness is indeed a factor that helps in fomenting earnings momentum as well as price momentum. However, it is important to note that controlling for information discreteness in the tests does not appear to weaken the role of my consistency/streakiness in earnings proxy in determining the extent of recorded quarterly earnings-driven momentum observed in my data sample.

In chapter 5, I employ alternative metrics to measure change in investors' expectations of earnings and the impact of earnings streaks on market returns for three days around the quarterly earnings announcement date. Earnings surprises are calculated in every quarter in my sample by subtracting the monthly analysts' forecast of quarterly EPS from the actual EPS reported in the current quarter and then scaling by the prior year end stock price. To ascertain the impact of streaks of positive and negative quarterly earnings surprises on stock returns in a shorter window, I employ the three-day buy-and-hold Fama-French three-factor adjusted returns measured for three days around the earnings announcement date. In this chapter, I ask if the streaks of quarterly earnings surprises and reversals have significant impacts on post-earnings announcement drift over these three days. I also ask whether the

length of either positive or negative earnings surprises matters on the strength of its impact on post-earnings announcement drift. Furthermore, I ask whether information uncertainty conditioned on the streaks of earnings surprises exacerbates earnings-generated momentum in price. Does the gambler's fallacy influence the investor's response when he observes streaks of quarterly earnings surprises of a particular sign around quarterly earnings announcements? Does the impact of the gambler's fallacy weaken as the streaks of quarterly earnings surprise grow longer?

The findings from this empirical analysis strengthen the case for the informativeness of streaks of quarterly earnings surprises in explaining earnings momentum in stock returns. This is interesting, given that in this chapter, the investigation is carried out to test the explanatory power of streaks of earnings surprises in a shorter event window of three days - within the period when the effect of the nature of earnings news is most intense in the markets. Within this window, the magnitude of earnings surprises lacks any explanatory power, while the streak of earnings surprises maintains its explanatory power, thus supporting the claim that streaks of earnings surprises possess better explanatory power than any single earnings surprise arriving at the most recent earnings announcement. As Fama (1998) suggests, studies involving short event windows of, say, a few days have one obvious advantage in that the daily expected returns are very close to zero, therefore the choice of the model for measuring expected returns does not have much impact on the interpretation and inference drawn from the abnormal returns so measured. So the chance of a benchmarking or research method error confounding my reported results is far less in this empirical chapter.

Furthermore, the findings suggest that there is significant impact of streaks of earnings surprises on market returns in a three-day window around the earnings announcement date. Quarterly earnings reversals also have a significant impact on market returns at around the earnings announcement date. However, their impact is less pronounced and could be attributed to investors' reactions being less dramatic when a growing trend of quarterly earnings falls is terminated at the earnings announcement date. This result suggests that, although these companies are some of the most followed by analysts, are likely to have abundant information in the public domain, nevertheless; investors underreact when the sign of the earnings surprises suddenly changes. For those companies that show a positive earnings surprise in the most current quarter after several streaks of negative quarterly earnings surprise, investors' reaction is more muted, and this response might be a result of investors taking their time to digest the most current information in the earnings news. As the evidence from my results shows, there are more positive quarterly earnings reversals than negative reversals. This may not be unconnected to some sort of earnings management to

meet and beat targets characterising my S&P500 data sample. Some investors might think that this sudden change in the companies' woes must be transitory and will hardly last. The strength of the impact of streaks of earnings surprise tends to weaken as the streak in quarterly earnings lengthens for both positive and negative streaks.

There are a number of ways to describe the behaviour seen above. First, it might be explained in line with Rabin (2002b), who suggests that the effect of the gambler's fallacy begins to fade as the streak length grows. However, it is uncertain whether this also means that as Rabin and Vayanos (2010) suggest, another cognitive bias called the hot-hand fallacy is replacing the gambler's fallacy as the streaks grow even longer. Furthermore, it could also be suggestive of the fact that there is some form of learning going on among the investors. Investors might be interpreting increasing earnings rises to mean that those companies are engaging in some sort of earnings management. This may lead to more muted reactions from investors as the streaks continue to grow from quarter to quarter. However, the investors in companies posting consistent quarterly earnings falls over many quarters enjoy larger and positive returns for longer streaks than those posting consistent quarterly earnings rises for many quarters. This could also be suggesting that these companies are paying a premium to their long-suffering investors who are still holding their shares despite consistent quarterly earnings falls. Another reason could be that the shares of those companies with long streaks of quarterly earnings surprises falls become illiquid as time passes, and holders of such shares are unable to sell with the continual decline of the companies' earnings.

In chapter 5, the findings show that unconditional information uncertainty has little or no explanatory power for earnings momentum in returns. However, conditional upon streaks of earnings surprise, high information uncertainty exacerbates earnings momentum in those companies with positive streaks of earnings surprises, suggesting that streakiness and uncertainty are cumulative, rather than substitutive, in their mutual impact. For those companies that are young in the S&P500 index, are less highly capitalised by the market, or have high dispersion in their cash-flows, earnings momentum is exacerbated in their returns when they run streaks of positive earnings surprises. So the impact of streaks in earnings and information uncertainty about earnings announcements are clearly separable phenomena but have a cumulative effect. Earnings streakiness is a distinct element in the gradual dissolution of valuation uncertainty. On the other hand, since information uncertainty cannot explain returns, this implies that it cannot be attributed to risk which must be priced; rather it must be a behavioural characteristic of the firm.

Overall chapter 5 makes a number of contributions to the literature. First, the chapter shows that through the informativeness of streaks of earnings surprises, as Rabin (2002b) suggests, the gambler's fallacy could be the cause of underreaction/earnings momentum when companies report consistent earnings falls or rises. Again, the results suggest that there are potential portfolio trading strategies which could be exploited within the models employed in this chapter. Portfolio trading strategies which are long in stocks with positive streaks of earnings surprises, funding their purchase by going short in stocks with streaks of negative earnings surprises, appear to be profitable. Portfolio trading strategies which are long (short) in high uncertainty (low uncertainty) stocks when conditioned on positive streaks of earnings surprises are also profitable.

This study is one of the first to popularise the use of streaks of earnings surprises as a potential explanatory variable for earnings momentum studies. Furthermore, it is perhaps the first study to provide a clear theoretical basis for including a measure of earnings 'streakiness' in explaining stock market momentum. Chapter 5 also contributes to the debate on what exactly constitutes innovation in earnings news, as the shocks in quarterly earnings do not explain much. The confirmation or termination of a growing trend of quarterly earnings surprises seems to possess a stronger explanatory power. Therefore, as shown in chapter 4, the variable Consistency, or streakiness in quarterly earnings changes, possesses a stronger explanatory power than the simple absolute values of quarterly earnings changes. So, overall, the empirical evidence shared in my thesis has a number of implications both for the investor and for fund managers. In addition, it has investment implications for investors and fund managers to time their investment by investing in different stocks considering the streak lengths of such stocks. This should also inform the holding period of the portfolios so formed in this manner.

6.3 Limitations

It is important to state that this study, just like any other empirical research, is limited in its conclusions and inferences. A number of specific shortcomings identified in the empirical chapters are discussed in this section. I encourage the reader to pay attention to the identified limitations while interpreting the results and evidence shown in the empirical chapters.

In every empirical research study in the social sciences, it is always crucial to state the limitations of the sample data used in carrying out the research. The quarterly earnings data used for this work are from the I/B/E/S database. Although I did not winsorise, I did delete EPS changes data of 200% and above which most likely are a result of errors in the database. There is also the issue of missing data in the various datasets which I used. This

study adopts a number of proxies to capture information uncertainty surrounding the value of my S&P500 constituent stocks. The stock price data and other data used in constructing the information uncertainty proxies are from the Thomson Financial DataStream database. Inasmuch as these proxies are the ones prevalent in the literature, there is no consensus in the literature as to what should be the proxy for information uncertainty. Indeed there is a tension between attempting to capture true Knightian uncertainty, which precludes the construction of a probability distribution based on past events, and the sort of statistical inference I conduct here. It is therefore possible that each of these proxies on their own might capture more than one firm characteristic. It is also likely that an information uncertainty proxy's suitability for capturing a particular form of uncertainty might be limited. However, jointly, information uncertainty proxies could provide sufficient power to capture the effects of information uncertainty in stock returns. For instance, the evidence from my results shows that information uncertainty proxies such as market capitalisation, analyst following, and company age capture similar kinds of information uncertainty. These control variables might also interact and confound other controls that I employ such as the Fama-French three-factor 'risk' adjustment with its 'small minus big' premium prominent in the model's power. The use of standardised databases also means that, as in all cases where secondary data is used for investigation, the results from the data are only as good as the underlying data themselves. Furthermore, the common use of S&P500 companies suggests some degree of 'data snooping' in my study, since I draw on previous results derived from very similar data.

In both chapters 4 and 5, one cannot accept the behavioural explanations given as definite. This is because it is very difficult to say for certain whether one or two cognitive biases and/or heuristics are responsible for the underreaction that leads to earnings momentum in market returns. As in all empirical behavioural finance studies, it is important to approach the explanations offered with caution, knowing that in reality, the underreaction could have occurred as a result of mixture of a number of cognitive biases and heuristics interplaying simultaneously. Nor should the impact of the main risk-adjustment and market microstructure issues that standard finance tends to concentrate on be minimised in the hurry to assert the authority of behavioural insights. This is especially true while we await a single unifying theoretical framework for behavioural research in asset pricing. The conclusions and inferences drawn from the results should be treated as speculative, as it is difficult to exclusively test for a particular behavioural trait. The problem posed by the joint hypothesis of the efficiency of the market and a particular asset pricing model should be considered when reading the results of the empirical chapters. The test for zero abnormal returns directly invokes this joint hypothesis problem, which remains unresolved in my work.

This is because it is not possible to state with certainty that my findings are not due to some omitted risk control variables in my models.

My period of study covers a relatively short period (1991 to 2006). Some points to note from this are the following: first, the data sample is somewhat old and comes from highly capitalised companies in the United States, which is a mature market. Many well-established markets, such as the Cairo or Beijing markets, have had far more disruptive histories which are certainly equally worthy of study. My findings may be specific to this period and may not be representative of other periods. Second, it is possible that the results are peculiar to the United States and not anywhere else.

Third, I use the Fama-French three-factor model as my benchmark model to calculate abnormal returns. Although this is a popular benchmark model in similar empirical studies, there is no consensus that this model correctly captures true expected returns or that these factors are truly risk proxies, as opposed to measures of asset mispricing. Moreover, in the first empirical chapter, the buy-and-hold abnormal returns were calculated over the three months adjoining two quarterly earnings announcements. Therefore, it might not be completely accurate to assume that no other firm-specific news filtered into price during this period. Earnings momentum in this medium term might just be one of the factors driving momentum in stock returns. This would require me to enhance my benchmark to include Carhart's (1997) momentum factor.

6.4 Further research work

The results of this thesis show that there is enormous potential research that could be carried out in the area of earnings momentum and its models. My thesis is a departure point as well as an end point in my academic life. In some sense, it is the end of a beginning and not the beginning of an end. There are now quite a few theoretical papers proffering predictions on how investors behave when they are under the influence of certain cognitive biases and heuristics when observing particular firm fundamental variables such as quarterly earnings outcomes. This brings together different theoretical and empirical research issues in economics, finance, psychology, and the financial markets in general.

First, this empirical study focuses on the United States market which is a much more mature, long-lasting market with companies having the largest market capitalisation. This research can be developed further by investigating other markets outside the United States and also including companies that are not as highly capitalised as my S&P500 constituent companies.

In a recent paper, Rabin and Vayanos (2010) suggest not only that the influence of the gambler's fallacy on investors weakens as the streaks of earnings surprises lengthen, but that simultaneously, another bias, the hot-hand fallacy, takes over at some trigger point in the sequence. According to the authors, this happens at the point when the investor might begin to learn that he is under the influence of the gambler's fallacy. However, the learning is wrong, as it leads the investor into the trap of committing simply another error; the hot-hand fallacy. It will be interesting to investigate this prediction to see if it is supported by empirical evidence.

Furthermore, the evidence from the results of this thesis shows that investors pay extra attention to news events that are repetitive in nature and also take into consideration the distribution of the signals. It will be interesting to examine how this model could be applied for further empirical research on price momentum and its earnings-based component.

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