Investor Sentiment and Herding

– An empirical study of UK investor sentiment and herding behaviour

By

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Abstract

The objectives of this thesis are: first, to investigate the impact of investor sentiment in UK financial markets in different investment intervals through the construction of separate sentiment measures for UK investors and UK institutional investors; second, to examine institutional herding behaviour by studying UK mutual fund data; third, to explore the causal relation between institutional herding and investor sentiment. The study uses US, German and UK financial market data and investor sentiment survey data from 1st January 1996 to 30th June 2011.

The impact of investor sentiment on UK equity returns is studied both in general, and more specifically by distinguishing between "tranquil" and "financial crisis" periods. It is found that UK equity returns are significantly influenced by US individual and institutional sentiment and hardly at all by local UK investor sentiment. The sentiment contagion across borders is more pronounced in the shorter investment interval.

The investigation of institutional herding behaviour is conducted by examining return dispersions and the Beta dispersions of UK mutual funds. Little evidence of herding in return is found, however strong evidence of Beta herding is presented. The study also suggests that beta herding is not caused by market fundamental and macroeconomic factors, instead, it perhaps arises from investor sentiment. This is consistent between closed-end and open-ended funds.

The relation between institutional herding and investor sentiment is investigated by examining the measures of herding against the measures of investor sentiment in the UK and US. It suggests that UK institutional herding is influenced by investor sentiment, and UK institutional sentiment has a greater impact as compared to UK market sentiment. Open-end fund managers are more likely to be affected by individual investor sentiment, whereas closed-end fund managers herd on institutional sentiment.

Keywords: Investor sentiment; contagion; institutional investors; equity returns, herding behaviour, investment decisions

JEL Classification: G02, G11, G12, G14, G15, G23

Table of Contents

List of Tables

List of Figures

Abbreviations

AAII:	American Association of Individual Investors
AIC:	Akaike information criterion
AVDC:	Advances-Declines Ratio
CBOE:	The Chicago Board Options Exchange
CCI:	Consumer Confidence Index
CCK:	Chang, Cheng, and Khorana (2000)
CEFD:	Closed-end fund discount
CH:	Christie & Huang (1995)
CSAD:	Cross-sectional Absolute Deviation
CSSD:	Cross-sectional Standard Deviation
EMH:	Efficient Markets Hypothesis
HS:	Hwang & Salmon (2004)
II:	Investors Intelligence
IOP:	The growth of UK index of production
MFI:	Money Flow Index
OEIC:	Open-ended Investment Company
OLS:	Ordinary Least Squares
ONS:	Office for National Statistics
PCV:	Put-call volume ratio
PCO:	Put-call open interest ratio
RSI:	Relative Strength Index
VOLA:	Realized volatility
NIPO:	Number of Initial Public Offer;

Chapter 1 Introduction

1.1 Background and Motivation

Between 2007 and 2009 the world witnessed a series of failure of large financial institution that led to a prolonged recession. The financial crisis was the worst since the Great Depression and caused significant damage to the economy worldwide. Many causes for the financial crisis have been suggested, one of which was that too many financial firms acted recklessly and took on too much risk. Prior to the crisis, the US housing bubble caused securities tied to US real estate pricing to be overvalued. 'Irrational Exuberance' encouraged financial institutions to increase their appetite for risky investments. The over-leveraged capital structure reduced financial institutions' resilience in case of losses. When the housing bubble burst, prices of linked securities plummeted, damaging financial institutions globally. Financial institutions, once seen as producers of economic efficiencies, became corroded components for economic and financial stability. The crisis has led to a re-examination of many of the sophisticated economic assumptions and financial theories, which includes a rethinking of the market efficiency hypothesis.

Under traditional finance theories, market participants are assumed to correspond to rational 'economic man', and the markets are informationally efficient (Fama, 1970). Assets are therefore valued rationally at their fundamental value, i.e. asset prices are the discounted stream of expected cash flows, and securities are traded in a market where all available public information is incorporated into asset prices. The markets correctly interpret all the information allowing prices to converge to fundamental values instantaneously. Any valuation that deviates from the fundamentals by 'irrational' traders, if any exist in the markets, will be eliminated by rational arbitrageurs who are supposed to know the real value of assets and take advantage of mispricing in the market. Assets should be priced at their fundamental value exactly, and no mechanism should allow the price to be driven away from this value for sustained period. The returns of assets are unpredictable since all available information has been incorporated in the asset prices. Prices should behave like independent random walks, and returns from time to time should be normally distributed.

From the 1980s, empirical studies of financial markets have raised numerous anomalies and puzzles, where asset prices, volatility and returns do not behave as described by these theories, but in a manner that traditional finance theories struggle to explain. For example, stock price momentum in the short horizon, (Bernard and Thomas, 1990; and Jegadeesh and Titman, 1993), and mean reversion in the long run, (Debondt & Thaler, 1985); excess price volatility in financial markets (Shiller, 1981; LeRoy et al., 1981); and leptokurtosis and clustering in the return distributions (Mandelbro, 1963). In order to explain the various financial market anomalies and puzzles, scholars have extended their research to market participants, utilising concepts, from Psychology and Sociology to describe the behaviour of asset prices based on aspects of investors' behaviour. These studies, involving the analytical modelling and empirical investigation of the 'human dimensions' of investment decision-making, have become a research strand known as Behavioural Finance. Investor sentiment is one of its pillars, providing an alternative theory of how investors form their beliefs about the market and future securities prices.

Equity pricing is the central issue for finance and there is a growing body of literature providing theoretical and empirical evidence that investor sentiment is a factor that influences asset prices. However, as it is an unobserved variable, obtaining a good measure of investor sentiment has become one of the main tasks in empirical research of behavioural finance. In academic research as well as industry practice, many indicators are used to accurately measure investor sentiment. Different measures and consequent outcomes have their distinctive advantages and drawbacks. This leads to the first research question of this thesis:

Research Question 1:

How can investor sentiment be measured and is investor sentiment contagious?

To answer the question involves a classification and evaluation of existing sentiment measures. It involves comparing sentiment measures with each other and their relation to other market parameters such as returns. Some new proxies are identified as components in the construction of a new measure of investor sentiment. As the study focuses on UK financial markets, a new set of investor sentiment measures are constructed to measure UK investor sentiment. This includes a measure for the overall market sentiment and a measure for UK institutional sentiment. Whilst the financial markets are increasingly integrated internationally, investor sentiment is expected to be contagious across borders. Therefore, the relationship between UK investor sentiment and foreign investor sentiment is investigated, and the empirical studies suggest that UK investor sentiment is influenced by foreign, particularly, US investor sentiment.

The availability of two new constructed UK investor sentiment measures warrants the analysis of whether UK equities are priced under the influence of investor sentiment. This leads to the second research question:

Research Question 2:

Are prices of UK equities affected by investor sentiment, and how does the sentiment of different groups of investors influence equity prices?

To answer the first part of the question, equities are categorized into three different size groups. The impact of investor sentiment on UK equity prices is examined, but the thesis also investigates whether the size effect on equity pricing is caused by investor sentiment. In order to answer the second part of research questions, the sentiment of individuals as well as institutional investors is brought into the analysis. This is the first time that UK institutional sentiment has been systematically measured and formally examined for its effect on equity pricing. According to the survey by the Office for National Statistics (ONS), by the end of 2010, institutional investors owned 47.3% of UK quoted shares and foreign investors owned 41.2% of the value of the UK stock market[1]. Foreign investor sentiment is therefore expected to have some explanatory power over UK equity prices, hence adding more information to the answer to the second part of the question.

Institutional investors are often seen as representative of rational arbitrageurs; however, empirical evidence suggests that psychological biases have been involved in institutional investors' decision making. When financial institutions' reckless behaviour contributes to one of the worst economic crisis in modern history, the behaviour of institutional investors comes under spotlight. One of the most typical examples is that

[1] Source from: Share Ownership: Ownership of UK quoted shares 2010, www.statistics.gov.uk

related to the phenomenon of investor psychology known as 'crowd behaviour'. This is usually termed 'herding' in the literature. This leads to the third question of the thesis:

Research Question 3:

Do institutional investors herd, and is this caused by sentiment?

In order to answer these questions, a study of institutional herding is conducted by examining herd behaviour from UK mutual funds portfolio returns. One rationale for institutional investors herding is that the reward structure for fund managers encourages them to form their investment portfolios by imitating the benchmark portfolio, normally the market portfolio, as the returns on the benchmark are often used to assess fund managers' performance. Therefore evidence of returns of mutual funds tending to cluster around market returns can constitute possible evidence of herding. The second part of question is answered by directly examining institutional herding measures against the investor sentiment measures. This enables the investigation of how institutional herding behaviour can be explained by the sentiment of different groups of investors.

This thesis joins the field of Behavioural Finance studies, and provides empirical evidence of investor sentiment effects on asset prices by utilising UK financial market data. At the same time it gives weight to the discussion of institutional investor sentiment and behaviour, filling a gap where UK institutional sentiment and behaviour have not been empirically studied in the past. It also proposes new measures for investor sentiment and directly investigates how investor sentiment influences institutional investor herd behaviour.

1.2 Structure of the thesis

The remainder of the thesis consists of 6 chapters organised as follows:

Chapter 2 reviews the relevant literature on investor sentiment studies. This begins with a brief of summary of the Efficient Markets Hypothesis (EMH) and the challenges to EMH theoretically and empirically. Investor sentiment approaches are introduced, including psychology based models and noise trader models, followed by a survey of empirical work on investor sentiment, which includes the measurement of investor sentiment.

Chapter 3 empirically studies UK investor sentiment. This begins by constructing a UK investor sentiment index at a weekly frequency. The composed investor sentiment indexes are then used to examine the relationship between UK investor sentiment and foreign investor sentiment. The effect that investor sentiment has on UK equity returns is also investigated in this chapter. The analysts are also conducted on a monthly frequency.

Chapter 4 reviews investor herding behaviour. The review of herding theories concentrates on the cause of herd behaviour and establishes how herd behaviour affects asset pricing. Empirical work includes investigating return-base herding and micro-level herding to provide evidence of herd behaviour of investors.

Chapter 5 studies UK institutional herd behaviour. It begins with investigations of herding behaviour in UK open-ended and closed-end funds by using daily, weekly and monthly data. The examination of UK institutional herd behaviour is conducted by using three different methods. Herd behaviour is also analysed in different stages of the financial crisis and under different market conditions. The using of different frequency data in the study of UK institutional herding behaviour provides a comparison of the analysis.

Chapter 6 studies the relationship between UK institutional herding and investor sentiment, particularly the causal relations of investor sentiment to herding. Open-end fund herding and closed-end fund herding are both examined. It also involves two time frequencies, weekly and monthly, to examine the relationship.

Chapter 7 summarises the findings in the study. It contains a distillation of contributions that the study has made and proposes future research questions.

Chapter 2 Literature review

2.1 Introduction

In the last four decades, the EMH has been the core theory in finance studies. The proposition rests on three basic arguments: firstly, investors are assumed to be homogeneous and rational, and therefore securities are priced rationally in the market. It may be that some investors are in fact not rational, therefore secondly, if irrational traders' activities are randomly on either side of the market they will cancel each other out, which would not affect the efficiency that security prices fully reflect all available information. Thirdly, if irrational investors act on the same side of the market, they are confronted by rational arbitrageurs who are supposed to be able to dominate the market by their scope and scale, and therefore eliminate these irrational influences on security prices by taking advantage of the mispricing resulting from irrational activities (Shleifer 2000). The impact that irrational investors would have on security prices and returns are therefore insignificant and very short-lived. Friedman (1953) stated that any deviation from the fundamental value, i.e. mispricing, will create an investment opportunity for riskless profits. Rational traders, i.e. arbitrageurs, will immediately snap up the opportunity, thereby restoring fundamental (equilibrium) price.

Empirically, the EMH has been categorised into three forms depending on the nature of the information. The weak-form of market efficiency posits that past prices cannot predict future prices. Fama (1965) found that stock prices follow random walks, i.e. the current changes of security price are independent from their previous changes; therefore trading strategies, such as chasing price trends would not be profitable. The semi-strong form of market efficiency states that asset prices adjust to new public information immediately. The pioneering event-studies of Fama, Fisher, Jensen, and Roll (1969) demonstrated that important corporate news events were incorporated into share prices immediately at the time of public announcement. The strong form of EMH expresses that, even when trading on inside information, investors are still not able to make profits, because the insider's information is quickly leaked out and incorporated into security prices.

2.2 Challenges to Efficient Markets Hypothesis

2.2.1. Theoretical Challenges to EMH

With respect to the three basic market efficiency assumptions, behavioural finance poses challenges from psychological experimental evidence for investor rationality and the scope for arbitrage. If efficient theory stands entirely on the assumption of the rationality of investors, the question of whether investors are fully rational would by itself present a considerable challenge for the theory.

1) *Are investors fully rational?*

In standard finance studies, economic agents are assumed to be fully informed, calculate with Bayesian laws and maximise expected utility, i.e. they are fully rational in processing information and forming decisions. Sentiment has not been left space in decision making and economic activities. The idea of the strictly rational behaviour of economic agents has long been debated in economic research. Hayek (1952) stated that nobody can be fully knowledgeable, and the limitation of knowledge is unavoidable leading to errors appearing in the decision making no matter how 'rational' the calculations people have applied. Kahneman & Tversky (1973) point out that when a decision is made under uncertainty, the calculation of expected returns could divert from Bayesian rules and other probability theories. Coase (1988) criticised the perfect rational 'economic man' assumption, and called the economic theories constructed under fully rational assumptions as 'blackboard economics'. Simon (1991) defined the term of bounded rationality to designate the rational choice which is constrained by taking into account the cognitive limitation of both knowledge and capacity. Even though economic agents try to work in a rational way, their ability to be rational is restricted either by the knowledge they have or the resources available to them.

The concept of bounded rationality has been widely extended in behavioural finance studies. The information limitations, resource restrictions, and cognitive bias, limit investors' ability to adopt the optimal solution. Intuition, mood, and/or emotion are involved in the processes of decision making consciously or unconsciously Therefore economic agents cannot always act fully rationally and reach perfect decisions. In many finance studies, any non-rational beliefs, preferences or behaviours are simply defined as irrational. In economic studies, the assumption of limited rationality can be broadly categorised as: exogenous or endogenous.

(1) Exogenous limited rationality is fairly similar to Simon's bounded rationality. It is that the individuals are following 'rational' rules, but the resources, such as information, time, knowledge, or finance, available to them are not sufficient. This can restrict their activities from being fully rational, resulting in under- or over-reactions in the markets. Examples of such investors are noise traders in the Black (1986), and Kahneman and Riepe (1998) models, sometimes called 'irrational' investors in economic studies. It can also be seen as a type of passive 'irrationality'.

(2) Endogenous limited rationality is that human beings' psychological characteristics or instincts are unavoidably involved in the collecting and processing of information, leading to systematic judgment errors in forming beliefs and preference, which in turn affect the valuation of securities. Psychological biases such as overconfidence, optimism, representativeness, conservatism, belief perseverance, anchoring, and so on, can be one or more of the factors that restrict economic agents from judging and behaving in a fully rational manner. Investors in the Odean (1998) and Daniel et al (1998) models, Barberis et al (1998), DeLong et al (1990) and Hong and Stein (1999) model are this kind of bounded rational investors.

Black (1986) and Kahneman and Riepe (1998) call the investors who trade on irrelevant information or deviate from the standard decision making models as noise traders. DeLong et al. (1990) refer to noise traders as those whose decisions are not based on an analysis of fundamentals but on sentiment. Investors' beliefs, preferences, emotions, or mood have been partially or fully involved in their investment decision making.

2) *Are irrational trades in the same direction?*

The challenge to the second EMH assumption concerns the direction of irrational trades. Kahneman, Tverskey and other psychologist experiments show that people mostly deviate from rationality in the same way rather than randomly, i.e. people are, very often, subject to the same cognitive biases and display the same "irrational" preferences. Whether they are sophisticated or unsophisticated investors, they form investment decisions based on their own beliefs and preferences, which may be subject to the same biases, and therefore their investment activities will be highly correlated. Under such a premise, they would not trade randomly with each other, but rather they will buy (or sell) the same security at probably the same time. Moreover, the sophisticated professional money managers, who manage other people's money, are agents active in the market on the behalf of the principles. This delegation introduces further distortions into their decisions and creates the incentive to herd in crowds, which means that when sophisticated investors take part in the irrational trades, the 'herd instinct' leads them to follow the trend and to take positions in the same direction rather than the opposite direction which will cancel out each other.

3) *How effective is arbitrage?*

When market efficiency entirely depends on the effectiveness of arbitrage, the ability of the arbitrageurs, who are not subject to psychological biases, to correct the sentiment investors' mispricing becomes vital. From a theoretical point of view, DeLong et al. (1990a) point out that when arbitrageurs take the opposite side to correlated sentiment investors and try to bring prices back to fundamental values, a new risk arises from such a position: the noise trader risk. This kind of risk manifests when prices are driven away even further by the sentiment investors after the arbitrageurs took their position. By taking up such risk, arbitrageurs could end up making losses and not being able to maintain their position. In this case, risk averse arbitrageurs would worry about the damages that possibly occur when price divergence becomes worse and not take up the opposite side to the sentiment investors. Arbitrage therefore is a risky process and may be of only limited effectiveness.

Furthermore, in the presence of feedback traders, who tend to chase price trends, rational investors tended to amplify rather than diminish the effect of sentiment traders (DeLong et al., 1990b). Rational investors speculate on the anticipation of further changes in asset prices caused by feedback trades, and try to make gains by "taking the ride". Therefore, they never choose to offset all of the effects of irrational investors. DeLong et al. (1991) also prove that for a plausible misperception, irrational noise traders can survive and dominate the market in terms of wealth in the long run, implying that the correction of mispricing by rational investors' arbitrage will be a long horizon process. Moreover, in the real world, as Shleifer and Vishny (1997) point out, the possibility of an early, forced liquidation would lead many arbitrageurs to have short horizons. This means that the arbitrageurs are not able to maintain their positions until prices return to their fundamental values. Their arbitrage power over prices again is limited. Keynes has a famous quote for the long-lived survival of effects from irrational traders: "Markets can remain irrational longer than you can remain solvent" ("When Genius Failed" (2000) by Roger Lowenstein, p. 123)

2.2.2. Empirical Challenges

Empirically, a body of evidence has presented a challenge to the traditional view that securities are rationally priced to reflect all publicly available information. These studies argue against Market Efficient Hypothesis in respect of the three empirical forms.

The weak form of the efficient markets hypothesis proposes that investors cannot make excess profits using past price information. A number of studies found positive short-term autocorrelation of stock returns, or 'under-reaction', and negative autocorrelation of long-term returns separated by long lags, or 'over-reaction'. For example, Bernard and Thomas (1990), Jegadeesh and Titman (1993) found that a stock's price seems to respond to earnings for about a year after they are announced, i.e. stock prices under-react to earnings announcements in the short-term. Debondt & Thaler (1985) discovered that over a long horizon of perhaps 3 to 5 years, the returns that were past winners would tend to be future losers, indicating that stock prices tend to overact on average in the long run. Subsequent to these findings researchers have identified many ways to successfully predict stock returns from past returns, which represent a departure from the conclusion that past returns have no predictive power for future returns under the efficient market hypothesis.

The semi-strong form of the market efficiency hypothesis has been challenged by a number of empirical deviations. The best known among them are the size phenomenon and 'January Effect'. Keim (1983) found that returns of small size stocks always outperform the market especially in the month of January. Shleifer (2000) also reviewed Siegel's work (Siegel, 1998) to show that historically the return on the smallest decile of the New York Stock Exchange stocks is 40.55% higher than that of the largest decile of stocks. Since the month and the size of firms are already known in advance, excess returns should not occur in semi-strong forms of efficient markets.

The basic efficient market proposition is that stock prices do not react unless new information materialises. However Shiller (1981) worked on stock market volatility and showed that volatility was far greater than could be justified by an efficient market model. The evidence regarding excess volatility implies that changes in prices occur not for fundamental reasons, but because of factors that might relate to investors sentiment. Cutler et al (1991) examine the 50 largest one day stock price movements in the US and find that more than news seems to move stock prices, which is broadly consistent with Shiller's finding; that is, except for fundamental information, the price of stocks also change with respect to "things as 'sunspots' or 'animal spirits' or just mass psychology" (Shiller, 2003, P. 84).

2.3 The Investor Sentiment Approach

In responding to the difficulties of applying efficient market theory to explain financial market anomalies, theories of individual and social psychology have been widely utilised in finance studies to examine the dedicated factors of asset pricing and its changes. The influences of human psychological and interacting behaviour on financial markets have become one of the important components in finance studies.

Two questions have been at the centre of behavioural finance studies, theoretically and empirically: how asset prices deviate away from their fundamental values; and why the deviations cannot be eliminated as suggested in the Efficient Market Hypothesis. Barberis and Thaler (2003) point out that behavioural finance has made significant advances with regard to two aspects: limited arbitrage and investor sentiment.

2.3.1. Limited arbitrage

Arbitrage is an investment strategy that investors simultaneously purchase and sell essentially similar or virtually the same securities in two or more different markets to take advantage of price differences and make a riskless profit at zero cost (Sharpe and Alexander, 1990). This concept has been extended further to include a combination of matching deals transacted by arbitrageurs, i.e. buying underpriced securities and selling those overpriced, to earn costless and risk-free returns. As a result of arbitrage, prices revert to their fundamental values. According to the definition, the conditions for unlimited arbitrage to be possible are: (i), the availability of perfect (or close) substitutes; (ii), the fundamental risk is not systematic; (iii), arbitrageurs have long horizons. A series of theoretical and empirical papers demonstrate the violations of these conditions, resulting in arbitrage being far from being riskless.

The most obvious risk an arbitrageur faces is that substitute securities are rarely perfect or even close (Campbell and Kyle, 1993). It is very difficult, in practice, to find a close substitute that is able to remove all fundamental risks by arbitrage. Moreover, the costs of security trading result in arbitrageurs facing implementation risks, especially, in the presence of short-sales. Shiller (2003) states that 'smart money', i.e. arbitrageurs, may be at risk when it is difficult to short a stock if the arbitrageurs no longer own the stock. Even without the constraint, the costs of establishing a short position make it less attractive, because the interest on borrowing may be greater than the security price decreases (Barberis & Thaler, 2003). Furthermore, some restrictions for short-selling, in practice, may come from legislation and regulation. For example, many pension fund and mutual fund managers are not allowed to short-sell. By potential exposure to the risks, arbitrageurs are reluctant to take action even if prices are not in equilibrium.

Apart from fundamental and implementation risks, there is also a new systematic risk that arises when the sentiment traders are too bullish and/or bearish. When arbitrageurs and sentiment noise traders interact in an economy, noise traders can have a substantial and long-life impact on asset prices (De Long et al. 1990, 1991; Shleifer & Vishny, 1997; Shleifer, 2000). This can be a limitation for arbitrage. If noise traders are too bullish (bearish) about a security, they buy (sell) it and drive the price up higher (down lower) than its fundamental value. Arbitrageurs then take short (long) position and hope the price reverses to the fundamental soon. However, if noise traders get even more bullish (bearish) and push the price up (down) further, arbitragers may have to liquidate their position in order to limit their losses. The fear of such scenarios may stop them taking an arbitrage position in the first place.

Moreover, DeLong et al. (1991) stressed that the long term survival of noise traders leads arbitrage to be a long horizon process. However, in the real world, the existence of agency relationships results in the separation of brains and resources. The agents, such as fund managers, are normally assessed by their short-term performance, leading to them have a short-horizon performance targets. The principal (revenue owner) they represented, therefore, acts as if he/she has a short horizon. The better informed fund managers (arbitrageurs), in this case, may worsen the noise traders' mispricing either acting in the anticipation of a short term price momentum, or being forced to liquidate their positions because the investors withdraw their funds in response to the short-term losses. The arbitrage again is limited.

2.3.2. Investor sentiment

It is believed that in the real world, economic agents make their investment decisions not only based on information and facts, but also on the influence of their intuition, cognitive psychology, and often on the comments and opinions of others. Kahneman, Tversky, Smith, and other psychologists have developed a series of experiments on human choices and decision making and incorporated them into economic and finance research. In 1970s, Kahneman and Tversky published a series of articles to propose Prospect Theory which completely changed the models of decision making from those of mainstream economic studies. They illustrate an 'S' shape change of preference stating that the value of the outcomes is assigned to a reference point (usually gains and losses) rather than the final wealth states (Kahneman and Tverskey (1979)). This means that instead of maximizing expected utility, the benchmark utility is applied in the valuation of option outcomes, (De George et al. (1999)).

Studies also show that psychological biases such as overconfidence, representativeness, and conservatism, may play roles in the formation of economic agencies' investment decisions. Several theoretical studies use psychological biases as a basic mechanism to establish the relationship between investors' sentiment and asset prices, and to explain some of the "abnormal" phenomena observed in financial market. For example, Daniel, Hirshleifer and Subrahmanyan (1998) emphasized that investor overconfidence and bias self-attribution can cause stock prices to over-react to private information and under-react to public signals. Barberis, Shleifer and Vishny (1998), consider conservatism and representativeness in models to explain stock price over- and underreaction. Hong and Stein (1999) assume two types of bounded traders: momentum traders and news watchers. The assumption stresses the fact that the price trends focussed on by momentum traders can be traced back to representativeness heuristic, whereas the overwhelming focus on private information by news watchers can reflect overconfidence bias. Behavioural finance emerged in responding to the limitations that traditional finance has had in explaining financial market anomalies. It provides an alternative theme to explore the financial markets, especially regarding the sentiment of the market participants and their consequent impact.

Broadly, investor sentiment is defined as '… a belief about future cash flows and investments that is not justified by the facts at hand' (Baker and Wurgler, 2007, p129). Investor sentiment is, therefore, defined as the theory of how people form their beliefs and preferences with cognitive bias, psychological bias, emotion and mood, and then predict future asset prices. This suggests that investor sentiment is derived from emotional reactions rather than fundamental changes in stock markets, and then influences the expectations of stock returns (Xu and Green, 2013). The role of investor sentiment has been formally modelled in determining an assets price. The sources of sentiment, however, are difficult to be identified and measured. Empirical examinations of the importance of sentiment are more likely to refer to speculation bias: excessive optimism or pessimism (Lee, Shleifer and Thaler, 1991; Brown, 1999; Brown and Cliff, 2004). These narrowly define investor sentiment in intuitive terms which represents the expectations of market participants relative to a norm which is justified by the facts (fundamentals). Bullish investors expect returns to be above the norm and bearish investors expect return to be below the norm (Brown and Cliff, 2004). Such definitions allow sentiment to be measured by either directly conducting a survey to capture how bullish or bearish investors are, such as Bull-bear spread from American Association of Individual Investors and Bull/Bear Ratio from Investors Intelligence, or using indirect proxies such as financial market bull-bear indicators, e.g. Advance-declines ratio and Relative Strength Index.

2.4 **Survey of Investor Sentiment Theories**

Investor sentiment refers to people's beliefs based on heuristics rather than Bayesian rationality (Shleifer, 2000), and the forming of beliefs is influenced by intuition, cognitive psychology, and very often, affected by emotions and/or mood. Baker and Wurgler (2007) stress that sentiment always has effects on an investor's decision making, and an impact on asset prices, volatilities and returns.

2.4.1. Psychological belief base models

The psychological experiments on human choices and decision making show that there is no obvious way of deciding which of the psychological elements are the most important in the forming of judgments and decisions. The studies, however, provide suggestive hints of how 'irrational' agents might tend to behave in an uncertain world. Firstly, they might wrongly weight certain information in perception of risks and opportunities. Secondly, the preference for risks might be strongly correlated across investors. Thirdly, they might fail to accurately assess information resulting in miscalculation of the expected returns.

Overconfidence

One of the best documented psychological biases is that individuals tend to underestimate variances and are excessively confident about their own judgments, (Einhorn& Hogarth, 1978; Lichtenstein et al, 1982; Kahneman et al, 1982). Psychological and scientific evidence has also suggested that overconfidence is more severe for diffuse and delayed feedback tasks, and experts are more certain about their predictions under such circumstances (Daniel et al, 1998). When subjective confidence is involved in investment decision making, investors tend to either overestimate information precision (Kyle & Wang, 1997; Wang, 1998) or overweight their private information (Caballe & Sakovice, 2003; Odean, 1998) and thus react to the information to a greater degree than their objective accuracy.

Odean (1998) and Daniel et al. (1998, 2001) model the overconfidence effects on asset prices and show that such investor sentiment leads to miss-valuation of private information, a subsequent deviation of the asset price away from the fundamental value and ultimately, the generation of positive serially correlated returns and excess volatility. They emphasise the psychological bias in the interpretation and valuation of private information leading to investors being over-confident about the private signals rather than public information, and overreacting to those private signals, driving stock prices away from the fundamental price. This deviation can be in both directions. If the private information is positive, overconfident investors will push prices up too far relative to fundamental values. When further public signals arrive, the overreaction will be corrected and result in the price changes being unconditionally negatively auto-correlated at both short and long lags, and volatilities around private signals being increased. Odean's models also indicate that overconfidence increases trading volume and induces greater liquidity.

In the basic model in Daniel, Hirsheifer, and Subrahmanyam (1998), the investors were assumed to overestimate the precision of private information signals. In a 3 period economy, they assume that a common noisy private signal, s_1, about the value of security is received by sentiment investors at day 1, and they trade with those who are uninformed. The private information signal is

$$s_1 = \theta + \epsilon \tag{2.1}$$

where, $\epsilon \sim N(0, \sigma_\epsilon^2)$, and θ is the terminal value of risky security, and $\theta \sim N\left(0, \sigma_\theta^2\right)$. Since rational investors, arbitrageurs, correctly assess the error variance, σ_ϵ^2 , but overconfident investors underestimate the error variance as σ_C^2, so $\sigma_C^2 < \sigma_\epsilon^2$.

At day 2, a noisy public signal, s_2, arrives, and it is $s_2 = \theta + \eta$. The noise, $\eta \sim N\left(0, \sigma_p^2\right)$, and it independents of θ and ϵ. All investors have correctly estimated the noisy public signal variance, σ_p^2 .

At day 3, a conclusive public signal arrived and the security converges to its terminal value: $P_3 = \theta$.

Assume the sentiment traders are risk neutral, and the expectation operator is calculated based on the sentiment investors' confident beliefs (denoted by the subscriptc). Prices in day 1 and day 2 are:

$$P_1 = \mathrm{E_c}[\theta|\theta + \epsilon] \tag{2.2}$$

$$P_2 = \mathrm{E_c}[\theta|\theta + \epsilon, \theta + \eta] \tag{2.3}$$

By standard properties of normal variables, prices in day 1 and 2 become:

$$P_1 = \frac{\sigma_\theta^2}{\sigma_\theta^2 + \sigma_C^2}(\theta + \epsilon) \tag{2.4}$$

$$P_2 = \frac{\sigma_\theta^2(\sigma_C^2 + \sigma_P^2)}{D}\theta + \frac{\sigma_\theta^2 \sigma_P^2}{D}\epsilon + \frac{\sigma_\theta^2 \sigma_C^2}{D} \tag{2.5}$$

where$D = \sigma_\theta^2(\sigma_C^2 + \sigma_P^2) + \sigma_C^2 \sigma_P^2$

Overconfidence in the private signal causes the price to overreact to the new information at day 1. This mispricing will be corrected on day 2 and 3 when public information signal arrives. The overreaction and correction imply that $cov(P_2 - P1, P1 - P0$ is negative and the covariance between day 1 and 2 price change is:

$$cov(P_2 - P_1, P_1 - P_0) = -\frac{\sigma_\theta^6 \sigma_C^2 \sigma_P^2(\sigma_\epsilon^2 - \sigma_C^2)}{(\sigma_\theta^2 + \sigma_C^2)^2[\sigma_\theta^2(\sigma_C^2 + \sigma_P^2) + \sigma_C^2 \sigma_P^2]^2} \tag{2.6}$$

Since $\sigma_C^2 < \sigma_\epsilon^2$, so $cov(P_2 - P_1, P_1 - P_0) < 0$, and the same process shows that $cov(P_3 - P_1, P_1 - P_0) < 0$. These illustrate that if investors are overconfident, the price moves resulting from private information are on average partially reversed in the long run, and price moves in reaction to the arrival of public information are positively correlated with later price changes.

The covariance between the day 2 and 3 price change is

$$cov(P_3 - P_2, P_2 - P_1) = \frac{\sigma_\theta^6 \sigma_C^2(\sigma_\epsilon^2 - \sigma_C^2)}{(\sigma_C^2 + \sigma_P^2)[\sigma_\theta^2(\sigma_C^2 + \sigma_P^2) + \sigma_C^2 \sigma_P^2]^2} \tag{2.7}$$

It is positive since $\sigma_C^2 < \sigma_\epsilon^2$. When the negative change above, between days 1 and 2 and days 1 and 3, are combined, it can be posited that if investors are overconfident, price changes are unconditionally negatively autocorrelated at both short and long lags.

Variances of the dates prove that the proportional excess volatility is greater around the private signal than around the public signal.

Another bias that appears in Daniel, Hirshleifer and Subrahmanyan (1998) is self-attribution. Self-attribution bias means that the outcomes confirm the investor's research. An asymmetric feedback effect was found from psychological experiments on people's confidence. It implies that the investors' confidence is strongly increased, when the public news confirms the investor's research, but there is no effect on confidence when public news rejects the investors' views. These result in positive short-lag autocorrelation and negative long-lag autocorrelation of price changes. Price changes also present positive short-term autocorrelation and negative long-term autocorrelation patterns.

Hong and Stein (HS, 1999), on the other hand, investigate the investors who process different sets of information and generate different private information. They demonstrate that stock prices appear to under react since the 'newswatchers' forecast stock prices based only on signals that they generated privately, and then slowly adjust to the 'fundamental' while private information diffuses gradually across the 'newswatchers' population, and the 'momentum traders' exploit this price underreaction by simply applying trend chasing strategies, which creates an eventual overreaction. DeLong et al. (1990) illustrate in an overlapping generation model that overconfident traders may have higher expected returns than rational traders in the same economy. Hirshleifer et al. (1994) suggest that overconfidence can promote herding in security markets.

Representativeness

Overconfidence can also be traced to the representativeness heuristic, as Tversky and Kahneman (1974) stressed that people try to categorize events as representative of a well-known class then, in making probability estimates, overstress the importance of the categorization. Consequently, people see patterns in data that are truly random and feel confident. Representativeness heuristic can lead to 'sample size neglect', i.e. the sample size has been neglected and a small sample has the same representativeness as a large one (Barberis and Thaler, 2003). It is sometimes known as the 'law of small numbers' (Rabin, 2002). One manifestation of the 'law of small numbers' in the stock market is that investors based on a history of consistent growth of earning, deduce that a firm is a growth company and ignore the fact that very few companies can keep growing. The investors in model 2 of Barberis, Shleifer and Vishny (1998), BSV henceforth, who believe in an earning trend, are subject to the representativeness heuristic. They associate past earnings growth too strongly with future earnings growth, therefore overreact to the information. It deviates the asset price away from its fundamental.

Conservatism

The conservatism heuristic states that individuals are slow to update new information into their beliefs. It suggests that investors cannot adjust their valuation of assets in response to the earning news fully and this leads to asset prices underreacting to the earning announcements. BSV incorporate conservatism and representativeness to show that investor sentiment prevents them from updating their valuation in the correct way, resulting in the asset prices under or overreacting to fundamental news and generating stock market momentum and excess volatility.

2.4.2. Problems of belief based models

Belief based sentiment models are constructed by applying the psychological biases to explain the finance anomalies. They model the decision problems of sentiment investors which endogenously generate trading mistakes that are correlated with fundamentals. In practice it is very difficult to decide which of the psychological elements is the most important in forming beliefs and preference. Therefore, the majority of belief-based models focus on one or two psychological biases that are commonly involved in forming beliefs and valuing the assets, and more generally affecting investors' demands for the assets, which finally influence the prices, returns, and volatility. Until now, there has been no single unifying model in behavioural finance for investor sentiment, therefore the impact of investor sentiment on the security prices, volatilities, and returns have been analysed by applying different forms of psychological biases in the studies. Empirically, it is an open question whether investors with certain psychological biases can be identified with a specific category of investors, such as institutional investors or individual investors. Moreover, most of the belief based models are very difficult to be directly applied and tested.

2.4.3. Noise trader model

Noise traders are the investors whose decision making process deviates from the standard models. They either trade on irrelevant information or make investment decisions based on sentiment rather than an analysis of the fundamentals. De Long, Shleifer, Summers, and Waldmann (1990) illustrate the importance of noise traders for price formation in their model. They point out that there is variability in price from the unpredictability of noise traders' future opinions. The model contains two types of investors in the market: rational arbitrageurs and noise traders.

Rational arbitrageurs, denoted as 'α', who accurately perceive the distribution of returns from holding the risky asset; and noise traders, denoted as 'n', who misperceive the expected price of the risky asset by an independent and identically distributed normal random variable, ρ_t, where $\rho_t \sim N(\rho^*, \sigma_\rho^2)$. Assuming that the market is populated by noise traders with a proportion of μ, and rational arbitrageurs which a proportion of $(1-\mu)$. The total demand for the risky asset is therefore composed by noise trader demand, λ^n, and arbitrageurs demand, λ^α.

The utility of the investors is a constant absolute risk aversion function:

$$U = -e^{-(2\gamma)\omega} \tag{2.8}$$

whereγ is the coefficient of absolute risk aversion, and ω is the expected final wealth.

With the agents maximizing their expected utility and the normally distributed returns, the demands for risky assets of arbitrageurs and noise traders respectively are functions of the price of the risky asset, the one-period-ahead distribution of it, and noise traders' misperception of the expected price of the risky asset:

$$\lambda_t^\alpha = \frac{r + {}_t p_{t+1} - (1+r)p_t}{2\gamma({}_t\sigma_{p_{t+1}}^2)} \tag{2.9}$$

$$\lambda_t^n = \frac{r + {}_t p_{t+1} - (1+r)p_t}{2\gamma({}_t\sigma_{p_{t+1}}^2)} + \frac{\rho_t}{2\gamma({}_t\sigma_{p_{t+1}}^2)} \tag{2.10}$$

Where p_t is the price of the risky asset; r is a fixed real dividend of the risk-free asset; $\rho_t$is noise traders' misperception; $\sigma^2_{p_{t+1}}$is the one-period-ahead distribution of the price of risky asset. [2]

Assuming that both noise traders and arbitrageurs are allowed to take short positions, the demands can be negative. Comparing the demand of noise traders to that of arbitrageurs, the extra term that appeared in equation (2.10) comes from noise traders' misperception of the expected returns. Noise traders' demands will be more than arbitrageurs' if they overestimate the expected returns and less than arbitrageurs' if they underestimate.

When the proportion of noise traders in the markets is μ, the proportion of arbitrageurs is $1 - \mu$. To calculate equilibrium, the price of the risky asset is formulated as:

$$P_t = 1 + \frac{\mu(\rho_t - \rho^*)}{1+r} + \frac{\mu\rho^*}{r} - \frac{(2\gamma)\mu^2\sigma_\rho^2}{r(1+r)^2} \qquad (2.11)$$

Where, μ is the proportion of noise traders, ρ^* is a measure of the average "bullishness" of the noise traders, and r is the riskless return.

Equation (2.11) shows that the equilibrium pricing function of a risky asset converges to its fundamental value of one if the noise trader's misperception converges to zero. The last three terms demonstrate the impact of noise traders on the price of risky asset. The second term in the equation shows that the variation of noise traders' misperceptions causes the fluctuations of the asset price. The larger the proportion of noise traders to arbitrageurs in the markets, i.e. the higher is μ, the more volatile asset prices are. If $\rho_t > \rho^*$, the generation of noise traders is more bullish than the average, they then bid up the price, and, if $\rho_t < \rho^*$, the generation of noise traders is more bearish than the average, they then bid down the price.

The third term in (2.11) illustrates that when noise traders' average misperception is different from zero, the price will deviate from its fundamental. The greater the level of

[2] According to DeLong et al (1990), maximizing the expected value of each agent's utility is equivalent to maximizing the expected final wealth, i.e. $E(U) = \bar{w} - \gamma\sigma_w^2$, where $\bar{w}$ is the mean wealth and σ_w^2 is the one-period-ahead variance of wealth. The arbitrageurs held the amount of λ^α risky asset to maximise the utility: $E(U) = \bar{w} - \gamma\sigma_w^2 = c_0 + \lambda_t^\alpha[r + {}_tp_{t+1} - p_t(1+r)] - \gamma(\lambda_t^\alpha)^2({}_t\sigma_{p+1}^2)$, and noise traders held the amount of λ^n risky asset to maximise the utility: $E(U) = \bar{w} - \gamma\sigma_w^2 = c_0 + \lambda_t^n[r + {}_tp_{t+1} - p_t(1+r)] - \gamma(\lambda_t^n)^2({}_t\sigma_{p+1}^2) + \lambda_t^n(\rho_t)$, where c_0 is a function of first-period labour income.

noise trader bullishness on average the higher is the price. A lower expected excess return is required by arbitrageurs since they bear a smaller share of price risk and therefore they are willing to pay a higher price. This ‘price pressure’ effect tends to lower noise trader’s relative expected returns.

The last term of equation (2.11) demonstrates how noise traders ‘create their own space’. When the risky asset, u, is believed to be mispriced in period t and the price, p_{t+1}, is uncertain, neither group is willing to bet too much on this mispricing. Arbitrageurs would not hold the risky asset unless compensated for bearing noise trader risk. For an asset that everyone agrees is overpriced, the return from increasing a position is offset by the corresponding additional price risk. Noise traders thus ‘create their own space’ and this space creation effect tends to raise noise trader’s relative expected returns.

The noise traders affect asset prices by trading when they are unusually bullish or bearish. When their activities are the collective consensus, the prices are driven away from fundamental values, and arbitraging short or long positions is now risky since the deviations could go further, therefore the rational traders choose to not fully restore prices and price volatility is increased by the sentiment of noise traders. Fama and French (2006) show that when misinformed investors drive the stock price away from the fundamental value by erroneous beliefs generated from the incomplete information they processed, informed investors will not fully offset the price effects from the misinformed when arbitrage is risky. It implies that the price effects from erroneous beliefs do not disappear until the beliefs of the misinformed converge to the beliefs of the informed, i.e. the beliefs are eventually completely in agreement.

2.4.4. The survival of noise traders

The model has demonstrated the impact on the price of the risky asset by noise traders trading when they are unusually bullish or bearish, however, Friedman (1953) pointed out that noise traders have the worst possible market timing, they buy high and sell low, and will earn lower returns then their rational counterparts, consequently, they are finally eliminated by ‘market natural selection’.

De Long, Shleifer, Summers, and Waldmann (1990) stressed that it is not necessarily the case that noise traders earn lower returns. The difference in returns between noise traders and arbitrageurs, ΔR_{n-i}, is the product of the difference in their holdings of the risky asset, $\lambda_t^n - \lambda_t^i$, and of the excess return paid by a unit of the assets. Therefore, the difference in returns is

$$\Delta R_{n-i} = (\lambda_t^n - \lambda_t^i)[r + p_{t+1} - p(1+r)] \tag{2.12}$$

Recall the equation (2.9) and (2.10), the difference in returns to the two types of agents at time t is:

$$(\Delta R_{n-i})_t = \rho_t - \frac{(1+r)^2(\rho_t)^2}{(2\gamma)\mu\sigma_p^2} \qquad (2.13)^3$$

and by taking the unconditional expectation of (2.13), it results in:

$$E(\Delta R_{n-i}) = \rho^* - \frac{(1+r)^2(\rho^*)^2 + (1+r)^2\sigma_\rho^2}{(2\gamma)\mu\sigma_p^2} \tag{2.14}$$

An obvious requirement for noise traders to earn higher expected returns in equation (2.14) is that the mean misperception of returns on the risky asset must be positive, i.e. $\rho^* > 0$. When the average misperception is positive, noise traders 'hold more' of the risky asset and raise market risk, thereby increasing their expected return. This is the so called 'hold more' effect. When the average misperception is negative, i.e. $\rho^* < 0$, there is no 'hold more' effect and $E(\Delta R_{n-i}) < 0$.

In equation (2.14), the first and second terms in the numerator incorporate the 'price pressure' and the buy-high-sell-low (or Freidman) effects respectively. When noise traders get more bullish, they demand more of the risky asset on average, and they buy the most of the risky asset just when other noise traders are buying it. The price is thus driven up and the return is reduced. However, the denominator in the equation incorporates the 'create space' effect, which tends to raise noise trader's relative expected returns. In order to take advantage of noise traders' misperceptions,

[3] Equation (2.9) and (2.10) imply: $p_t = \frac{1}{1+r}\left[r + {}_tp_{t+1} - 2\gamma({}_t\sigma_{p_{t+1}}^2) + \mu p_t\right]$; and the one-step-ahead variance of p_t is a unchanging function of the constant variance of a generation of noise trader's misperception ρ_t: $({}_t\sigma_{p_{t+1}}^2) = \sigma_{p_{t+1}}^2 = \frac{\mu^2\sigma_p^2}{(1+r)^2}$ (DeLong et al., 1990).

arbitrageurs need to bear the greater risk which arises because of the increase in the variability of noise traders' beliefs.

Though noise traders cannot earn higher average returns when they are too bullish since the price pressure effect increases with $(\rho^*)^2$, they can earn higher expected returns when average bullishness is at intermediate levels. Moreover, equation (2.14) show that the larger γ is, the greater the range of ρ^* is. This means that there are more risk averse agents in the market allowing the larger degree of bullishness for noise traders to earn higher average returns.

Further to this model, DeLong et al. (1991) also presented a model to illustrate that there are plausible misperceptions by noise traders allowing them not only to earn higher returns than do sophisticated investors, but also to survive and dominate the market in terms of wealth in the long run. The model assumes that noise traders tend to assess probability distributions, especially variances, poorly, which is supported by psychological evidence of the tendency to underestimate variances and to be overconfident. It proves two points; one, that noise traders who are more risk averse than log utility and misperceive variances by a small amount are guaranteed to survive in the market; two, that there are noise traders of many types who, despite misperceiving variances by a large amount, demonstrate faster wealth accumulation than rational investors.

2.5 Investor Sentiment Empirical work

The motivation of investor sentiment theories is to explain many of the empirical financial anomalies, such as Closed-end fund discount, excess volatility, price overreaction and underreaction. The development of sentiment theories provides a theoretical establishment of the relation between investor sentiment and asset prices, thus making some specific testable predictions of asset returns and volatility.

2.5.1. Investor sentiment and return

The noise trader models such as DeLong, Shleifer, Summers, and Waldmann (1990), suggest that subsets of investors may not make investment decisions based on market fundamentals and they are capable of affecting asset prices by way of unpredictable changes in their sentiments. This provides the theoretical hypothesis that the expected returns are affected by the degree of noise trader's average bullishness. Empirical evidence broadly agrees that even after controlling for "rational" influences such as mean-variance (Yu and Yuan, 2011) and Fama-French factors[4] (Xu and Green, 2013), indicators of sentiment do contribute significantly to explaining the time series and cross-sectional behaviour of stock returns in a variety of settings. Brown and Cliff (1999) find a strong correlation between sentiment and long horizon returns. In the study of short-horizon return reversals, Subrahmanyam (2005) finds that the relationship between current returns and lagged order imbalance is weaker than that between current returns and lagged returns, indicating that instead of inventory effect, belief reversal is more likely play a role in return predictability. Beaumont et al. (2005) conduct a joint test for the effects of individual and institutional sentiment on return and volatility in the German stock market. They found that stock returns increase when variations in investors' sentiment increase. Brown and Cliff (2005) found that sentiment is negatively related to stock returns, and the negative relationship is stronger for large or growth firms. Moreover, in horizons of a year or more sentiment is always more negative to returns than that for the next 6 months. They stressed that for larger or growth firms, sentiment is a significant predictor of future returns at the 1 - 3 years horizon. That stock returns increase when variations in investors' sentiment increase were found by Bandopadhyaya and Jones (2008). Wang, Keswani, and Taylor (2006) test the causal relationship between sentiment, return, and volatility. The results show that sentiment is Granger-caused by returns but not vice versa. Schmeling (2009) investigated the relationship between investor sentiment and stock returns by conducting a cross countries test. The study found that investor sentiment has a significantly negative impact on future stock returns, and the impact declines with the forecast horizon. In the study of how investor sentiment affects stock market crisis, Zouaoui, Nouyrigat and Beer (2011) estimate a logistic model by using panel data. They find that investor sentiment is negatively related to the future performance of stocks, i.e. when investor sentiment is low, subsequent returns are relatively high. They further find that within a one-year horizon, investor sentiment positively influences the probability of the occurrence of stock market crises.

[4] Fama and French (1996).

2.5.2. Investor sentiment and volatility

One of the implications of sentiment theories is that sentiment should correlate with excess volatility, since the variation of noise traders' misperceptions raises a systematic risk and further causes asset price fluctuations. Brown (1999) studied US close-end funds (17 funds for period 1993-1994) to investigate the direct relationship between investor sentiment and closed-end fund (CEF) volatility. He shows that unusual levels of investor sentiment are associated with not only greater volatility, but also heightened trading activities. Lee, Jiang and Indro (2002) estimate a GARCH-in-mean model to examine the impact of changes in investor sentiment on the conditional volatilities of the US major financial market indices (DJIA, S&P 500 and NASDAQ). They find the bullish changes in sentiment result in downward adjustments in volatility, and vice versa. Beaumont et al. (2005) found increasing variations in investors' sentiment increases conditional volatility in the German stock market. Wang, Keswani, and Taylor (2006) found that sentiment measures do not Granger-cause realised volatility, except ARMS[5] which produces the results that the causality has two way effects. Verma and Verma (2007) estimate a set of multivariate EGARCH model for DJIA and S&P500 returns. They find that sentiments have significant positive effects on stock returns, and negative effects on stock volatility. Han (2008) examines whether investor sentiment affects option prices and finds that the index option volatility smile is steeper (flatter) when investor sentiment becomes more bearish (bullish). In examining the relationship between investor sentiment and the stock index risk-neutral skewness, he finds that the index risk-neutral skewness becomes more (less) negative when investor sentiment is more bearish (bullish). The studies provide empirical support for the assumption that investor sentiment does correlate with volatility and suggest a negative effect of sentiment on volatility, i.e. bullish sentiment may lead to low volatility and bearish sentiment leads to high volatility.

2.6 **Measures of sentiment**

The question therefore, is no longer whether investor sentiment affects stock prices, but rather, how to measure and quantify the effects (Baker & Wurgler, 2007). This leads to a further empirical question of how to measure investor sentiment.

[5]ARMS index is also known as TRIN, was first published by Richard W. Arms, Jr. 1967. It is calculated by dividing advancing/declining ratio by up/down ratio. (http://quotes.wsj.com/UK/UKX/index-interactive-chart#Boolean)

One prevalent method is to use survey-based measures. These are referred to as ‘direct measures’. Survey-based measures are created by directly asking people about their expectations of the market, and so try to capture the mood of market participants. The surveys conducted by American Association of Individual Investors (AAII) and Investors Intelligence (II) are the most common such surveys. AAII is conducted by targeting individuals. It is primarily interpreted as a measure of individual investor sentiment. On the other hand, many of the respondents for II are current or retired market professionals, and it is therefore interpreted as a proxy for institutional sentiment (Brown & Cliff, 2004). Brown (1999) uses AAII to investigate the direct relationship between investor sentiment and closed-end fund (CEF) volatility. Lee Jiang & Indro (2002) use II to examine the impact of changes in investor sentiment on conditional volatilities of stock returns. Brown and Cliff (2005),Verma & Soydemir, (2006) and Fong (2013) also use AAII and II as sentiment measures to examine the relationship between sentiment and stock returns. The Consumer Confidence Index (CCI) is another survey-based indicator used to measure investor sentiment. Schmeling (2009) and Beckmann et al. (2011) use CCI to conduct a cross-border test and they find that investor sentiment has a significant impact on future stock returns, and investor sentiment in one country affects stock return in another country by passing the sentiment across.

The advantage of survey-based measures is that they come from primary data by directly asking about people’s thoughts and expectations of the market. They try to capture the mood of market participants and in this respect should be able to produce a very precise indicator of sentiment. However, there are well-known problems with survey measures that can influence the results obtained. For example, the possible errors in questionnaire, interview, or respondent can directly affect the quality of the results. Another disadvantage of survey-based measure is the low-frequency of the sampling period. Though many surveys are conducted on a monthly basis, and some on a weekly basis, they are still not of a fine enough granularity to relate short term sentiment to daily trading or intraday events. More importantly, surveys rely on respondents giving a true indication of their activities, but, very often, people may not do what they say they will.

Another method is to use certain financial market indicators as proxies to measure investor sentiment. The measures are normally the variables based on financial theories and created from financial data. They have been categorized into four groups by Brown and Cliff (2004). The first group of measures consists of variables based on recent market performance, such as the ratio of the number of advancing issues to declining issues, which is widely used as a sign of bullish (bearish) market sentiment in practice. The second group consists of variables that relate to particular types of trading activity, for example, the percentage change in short interest, which is seen as a representation of how bearish the market is. The third group relates to derivatives trading activity, for instance, the ratio of put/call trading volumes, which has been used by technical traders for years as an indicator of the market sentiment (Wang, Keswani & Taylor, 2006).The last group is those who do not fall into the first three categories, such as, Closed End Fund Discount and Mutual fund flows. These financial variables are viewed as 'market weather vanes' by financial market commentators. Brown and Cliff (2004), using US survey sentiment indices, establish some relationship between the variables and investor sentiment and construct sentiment indices by using financial variables. Financial market indicators are measured with a relatively high degree of accuracy and are supported by finance theories. They are also available in higher frequencies. However, the link between theory and data can be quite weak and relies heavily on their respective interpretation.

A third method is to compose a sentiment index from economic and financial market variables. For example, Brown and Cliff (2004) and Baker and Wurgler (2006) extract the common factors of the sentiment proxies to build investor sentiment indices from selected sentiment proxy variables; Bandopadhyaya and Jones (2006) construct the Equity Market Sentiment Index for a group of firms in an equity index; Chen, Chong, and Duan (2010) compose an index for Hong Kong investor sentiment; Chen, Chong and She (2014) compose one for Chinese investor sentiment; Baker, Wurgler and Yuan (2012) and Bai (2014) build indices for global investor sentiment. This method overcomes the low frequency and possible inaccuracy of survey-based measures, and the weak link between theory and data of financial indicators, although the methods for constructing sentiment index can be controversial.

One of the important assumptions of sentiment models is that the financial markets consist of different groups of investors. They are classified as 'informed' investors (or arbitrageurs) and 'uninformed' investors (or noise traders). However, in reality it is difficult to directly identify who are arbitrageurs and who are noise traders. For simplification, institutional and individual investors are among the most general classes of groups, representing arbitrageurs and noise traders respectively in empirical studies. Examples of institutional investors are mutual funds, hedge funds, pension funds, bank trust departments and other investment organisations. Compared to individual investors, they operate in large volumes of capital and are well equipped with information, facilities, and skilled analysts and traders. They are usually thought of as the ‘informed’ investors (or arbitrageurs) in the market who are assumed to try to trade securities on fundamentals, and take advantage of mispricing by uninformed investors (or noise traders), resulting in asset prices being restored to the fundamental value. Individual investors, on the other hand, are assumed to be the ‘uninformed’ investors, who make decisions with sentiment factors or trade on noise information. Most empirical studies of sentiment concentrate on an examination of the relationship between individual sentiment and market factors such as volatility and returns. However, Brown and Cliff (1999) found that institutional sentiment has a distinct effect in the market that differed from that of individual sentiment, and that institutional sentiment has a strong link with the returns of large stocks. Jackson (2003) tested order imbalance based on net flows into or out of Australian equity markets and found that larger trading of institutional traders in certain stocks increased conditional volatility, but that there was no such relationship between trades of individual traders and volatility. After estimating a multivariate EGARCH model for DJIA and S&P500 returns, Verma & Verma (2007) find that both individual and institutional investor sentiment have significant effects on stock market returns and volatilities, and individual investor sentiments react to institutional investor sentiments but not vice versa.

2.7 Conclusion

As a new research field, behavioural finance emerged from debating the theory of efficient markets. The assumptions of traditional finance theories have ruled out the consideration of investor sentiment, and its research themes defined how markets should behave rather than how markets actually behave. The limited role that traditional finance has played in explaining the market anomalies has led to the development of studies of the effects from market participants’ sentiment and behaviour, especially with regard to asset price and returns. In order to answer the core questions of how asset prices deviate away from their fundamental values and why the deviations persist, psychological and cognitive biases are incorporated into modelling investor sentiment and behaviour.

By considering investor sentiment, belief-based models, such as overconfidence models, illustrate the impact of investors' psychological biases on asset prices when they form their beliefs and preferences. Noise trader models show that sentiment based noise traders affect security prices by their average misperception, the fluctuation of misperceptions, and by introducing a systematic risk that could limit rational investors' arbitrage. These models are good at explaining some of the properties observed in financial markets such as, under- and over-reaction, excess volatility, booms and crashes. Despite its success, behavioural finance is criticised for failing to provide a general theory as traditional finance has done, and only ad-hoc models have been created to explain specific stylised facts.

Empirically, the centre of research has shifted to how to measure investor sentiment and quantify its effects on stock prices (Baker and Wurgler, 2007). Three methods are common. The first uses survey-based techniques which try to identify people's sentiment about economics and financial markets directly. The second method is to employ financial market indicators as proxies to measure investor sentiment indirectly. Third are composed indices, typically using principal components to extract a single sentiment measure from a variety of relevant economic and financial data. All three methods have their drawbacks. Surveys are expensive to conduct reliably at high frequency and "quick" questionnaires may produce answers which are less reliable. Financial market data are in theory more accurate but they involve a risk of circularity as they may simply reflect the outcome of share price movements rather than be an independent measure of sentiment. Finally, the use of principal components to create a composed index produces a variable which may not be very robust. The composition of the principal components may change as new data become available, implying that the entiretime series of sentiment may change over time. However, composed indices are probably the most popular of the three sentiment measures, particularly in studies of US data, arguably because they largely overcome the reliability issues of surveys and the independence issues of pure financial market data.

Chapter 3 UK investor sentiment measures

3.1 Introduction

After several decades' studies, investor sentiment has been recognised as an important component of the market pricing process and the focus has shifted towards identifying and quantifying investor sentiment. Measuring investor sentiment is not a straightforward task. Academic research and industry practices have identified and utilised various sentiment proxies to measure investor sentiment. These measures include sentiment surveys, mood proxies, general economic indicators, and financial market proxies; all are used to measure investor sentiment. Many investor sentiment measures have been identified in academic research and industry practices. However, the use of financial market proxies as instruments to measure investor sentiment is limited by how much the indicators are supported by the financial theories and how to interpret the linkage to the data. Brown and Cliff (2004) construct investor sentiment indices by using the principal component method and Kaman Filter method [6] respectively. The factor which is filtered out from selected market indicators is suggested to be a better measure by the consistency of analysis results from either method. Baker and Wurgler (2006) further identify six economic and market indicators and apply the First Principal Component method to build a market-wide sentiment index to measure investor sentiment. Both Brown and Cliff (2004) and Baker and Wurgler (2006) build their sentiment indexes based on the US economic and financial market variables. Both are seen as measures of US investor sentiment, especially the Baker and Wurgler (2006) index which is widely utilised by scholars for analysis of asset prices, such as Lemmon & Ni (2008), Kaplanski & Levy (2011), and Baker, Wurgler, & Yuan (2012) and Bai (2014).

Notwithstanding the popularity of this method, few composed sentiment indices have been constructed for the UK. In fact, the only two as far as we are aware is an annual market-wide index by Baker, Wurgler, and Yuan (2012), and a weekly market-wide index by Bai (2014) based on the Baker and Wurgler (2006) approach. Baker et al (2012) studiesthe long-term investor sentiment effect in the equity markets and Bai (2014) studies the short-term of sentiment effect. However, market anomalies, such as

[6] The principal component method and Kaman Filter method are described in Appendix 4.

the well known calendar effect of equity returns, suggesting that investor sentiment is also likely to affect returns in a medium run. London is one of the largest financial centres in the world and it has been the number one city in terms of financial flows in 2008.[7] There are very few studies that examine UK investors' sentiment and no survey-based investor sentiment measures available for the UK[8]. Therefore, a study of UK investor sentiment will make a contribution to the stream of research on investor behaviour and financial markets.

3.2 UK investor sentiment analysis

3.2.1. Summary of the Data

In order to capture the short-term effect of investor sentiment, the analysis of UK investors' sentiment is conducted on both a weekly and monthly basis. Various sentiment indicators are used in the analysis. These include the FTSE 100 index put/call ratio, trading volume, Closed-end fund discount (CEFD), realized volatility (VOLA), relative strength index (RSI), money flow index (MFI) and the advances to declines ratio (AVDC). Data for calculating these variables are collected from Datastream. In addition to the above proxies, the following are also included: number of initial public offerings (NIPO), collected from London Stock Exchange statistic reports;[9] consumer confidence index (CCI), collected from European Commission Economics Database and Indicators[10]; and mutual fund cash position (CFLW), collected from Morningstar database. However, these are only available at a monthly frequency. Foreign investors' sentiment proxies are also used in the analysis. They are: American Association of Individual Investors(AAII)[11]; Investors Intelligence (II)[12]; the Baker & Wurgler sentiment index (BWSI), collected from Jeffrey Wurgler's website[13]; German equity

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[7] Worldwide Centers of Commerce Index 2008, *Insights, Master Card Worldwide*

[8] TheEuropean Commission *Business and Consumer Surveys*for EU members is only available monthly and is concerned with general business and consumer confidence rather than investor or financial market sentiment.

[9] London Stock Exchange: http://www.londonstockexchange.com/statistics/home/statistics.htm

[10] European Commission Economics database & indicators: http://ec.europa.eu/economy_finance/db_indicators/surveys/time_series/index_en.htm

[11] American Association of Individual Investors: www.aaii.com

[12] Investors Intelligence: http://www.investorsintelligence.com/x/default.html

[13] Data source: http://people.stern.nyu.edu/jwurgler/

index (Sentix), data sourced from Sentix[14]; and German market indicator (GMI), collected from The Centre from European Economic Research[15].

Stock returns are another set of data used in the analysis. Equities traded in the UK markets are categorised into three portfolios according to their capitalisation sizes. The FTSE 100 Price Index, is used to represent prices of the large-size stock portfolio, and the return, R_{big}, is computed accordingly. The FTSE 250 Price Index represents prices of a medium-size stock portfolio, with return, R_{mid}. The FTSE Small Cap Price Index is used for a small-size stock portfolio, with return, R_{sml}. Data of the three price indices are collected from Datastream. Most of the samples range from 01 January 1996 to 30 June 2011, but a few variables, such as the German Sentix and the CFLW are not available for the full sample period. Therefore, the analysis is also performed on shorter sub-samples.

3.2.2. Definition and calculation of the sentiment proxies

Advances-Declines Ratio (AVDC): AVDC is usually thought of as a “Market Strength” indicator, and is calculated by using the number of stocks rising divided by the number of stocks falling in the market. It monitors the direction of the majority of stocks on the stock market, and it is used as sentiment within the stock market. Brown and Cliff (2004) and Wang, Keswani and Taylor (2006) both use a modification of AVDC to capture the relative strength of the market and form the part of investor sentiment index.

Closed-End Fund Discount (CEFD): The CEFD is one of the earliest indicators of market sentiment (Lee, Shleifer and Thaler, 1991). We calculate the discount from 129 closed-end investment trusts which are listed on the London Stock Exchange. The daily prices and Datastream-estimated Net Asset Values (NAV) are used in the calculation. The value-weighted discount of Lee *et al* (1991) is applied for the computation. They constructed a value-weighted index of discounts (VWD):

$$VWD_t = \sum_{i=1}^{n_t} W_i DISC_{it} \tag{3.1}$$

[14]Sentix: http://www.sentix.de
[15]The Centre for European Economic Research: www.zew.de

where:

$$W_i = \frac{NAV_{it}}{\sum_{i=1}^{n_t} NAV_{it}}, \quad NAV_{it} = net\ asset\ value\ of\ fund\ i\ at\ end\ of\ period\ t$$

$$DISC_{it} = \frac{NAV_{it} - SP_i}{NAV_{it}} \times 100,\ SP_i = stock\ price\ of\ fund\ i\ at\ end\ of\ period\ t$$

n_t is the number of funds with available $DISC_{i,t}$ and $NAV_{i,t}$ data at the end of period t.

Money Flow Index (MFI): Apart from RSI (see later), Chen, Chong, and Duan (2010)also include the Money Flow Index (MFI) in their construction of sentiment measure. The MFI is a momentum indicator to be used as a measure of the strength of money going in and out of a security, showing whether the security is overbought or oversold. Constructing the MFI begins with defining the “typical price” (TP) as an average of the high, low and closing price at time t, i.e.

$$TP_t = \frac{P_t^h + P_t^l + P_t^c}{3} \tag{3.2}$$

where, P_t^h is the highest price at t,, P_t^l is the lowest price, and P_t^c is the closing price. The money flow is then defined as: $Money\ Flow = Typical\ Price \times Turnover$. If $TP_t > TP_{t-1}$ then the money flow at time t is considered as positive. The total money flow over the previous N periods (N = 5 in this study) is calculated as:

$$MFI_t = 100 \times \frac{Positive\ Money\ Flow_t}{Positive\ Money\ Flow_t + Negative\ Money\ Flow_t} \tag{3.3}$$

The MFI varies between 0 and 100. It contains information of both price and turnover. Many practitioners use it as an indicator of the changing in the trend, when MFI moves in the opposite direction to the price.

Put-Call Volume ratio (PCV): The Chicago Board Options Exchange (CBOE) equity put to call trading volume is one of the most widely used to indicate investor sentiment. It is often used as a bearish indicator (Brown and Cliff, 2004). It is defined as ratio of the trading volume of put options to the trading volume of call options, i.e. $PCV =$

$\frac{volume_{put}}{volume_{call}}$. Wang, Keswani and Taylor (2006) utilise PVC for study of investor sentiment. Bandopadhyaya and Jones (2008) suggest that Put-call ratio is a better choice for measuring market sentiment compared to the Volatility Index (VIX).The PCV for the UK is calculated here by using FTSE100 index option put to call trading volumes.

Put-Call Open interest ratio (PCO): Wang, Keswani, & Taylor (2006) suggested that option open interest is likely to be a better predictor of volatility than PCV, and PCO is therefore a preferred measure of investor sentiment. For the UK we computed PCO, from the FTSE100 index option as the ratio of put open interest to call open interest.

Relative Strength Index (RSI): RSI is a market indicator showing whether the market is oversold or overbought. The market is thought to be overbought when RSI is greater than 80, and to be oversold when it is less than 20. Chen, Chong, and Duan (2010) suggest that RSI may be a proxy of investor sentiment, and use the RSI which is calculated from Hang Seng Index as a component to construct an investor sentiment index to measure Hong Kong investor sentiment.
The RSI is defined as:

$$RSI_t = 100 \times \frac{\sum_{i=1}^{n}(P_{t-1}-P_{t-i-1})_+}{\sum_{i=1}^{n}|P_{t-1}-P_{t-i-1}|} \tag{3.4}$$

whereP_t is the price at time t; $(P_{t-1} - P_{t-i-1})_+ = P_{t-1} - P_{t-i-1}$ if $P_{t-1} - P_{t-i-1} > 0$, otherwise $(P_{t-1} - P_{t-i-1})_+ = 0$. We use n = 14 as this is one of the most commonly-used indicators in the market.

Realized Volatility (VOLA): Brown and Cliff (2004) use the realized volatility calculated from Open-High-Low-Close data on the S&P 100 Index to construct an indicator of investor sentiment. Wang, Keswani and Taylor (2006) directly use the Realized volatility as a proxy to measure investor sentiment. The realized volatility measure used in this study is calculated by using the extreme value method of Parkinson (1980). The daily high and low of the FTSE100 index future prices is used to compute the weekly realized volatility. It measures investor expectations for market volatility as implied by the skew of FTSE 100 index future. A high VOLA indicates a low investor sentiment.

Trading volume (VRA): Baker and Stein (2004) suggest that market confidence is related to liquidity and argue that trading volume is a noisy measure of liquidity. We follow Baker and Wurgler (2006) and use a measure of the turnover ratio defined as:

$$VRA_t = 100 \times \frac{VOLMA5_t}{VOLMA50_t} \tag{3.5}$$

where $VOLMA5_t$ is the average turnover for the past 5 periods, and $VOLMA50$ is the average turnover for the past 50 periods. *VRA* turns out to be I(1), and therefore its first difference (*DVRA*) is used to help construct the sentiment indices..

3.2.3. Statistical summary of the weekly variables

Table 3.1 contains summary statistics of all the weekly variables. The sentiment indicator series displays a skewed and leptokurtic pattern and, except for the AVDC and the PCV, they all have high first order autocorrelation. All levels of weekly returns display excess kurtosis, negative skew and some serial correlation. The non-stationary nature of the variables is tested by using the Augmented Dickey-Fuller (ADF) test with 52 lags. The results show that only the trade volume, VRA, cannot reject the null hypothesis of unit root at the 10% significance level and the rest of the variables reject the null of having unit root at the 1% level. A further test of the first difference of the VRA has an ADF statistic value being significant at the 1% level, showing that the first difference of VRA (DVRA) is stationary.

Table 3.1: Statistics of Weekly Basic Data

Table 3.1 provides summary statistics of the basic data series. The data are weekly and cover the period 1st January 1996 to 30th June 2011 (809 observations). Exceptionally the *SENTIX* index is available only from 28th February 2001 (532 observations).

Variable definitions:
AVDC: Advances to declines ratio; **CEFD**: Closed-end Fund Discount; **MFI**: Money Flow Index; **PCV**: Put-call volume ratio; **PCO**: Put-call open interest ratio; **RSI**: Relative Strength Index; **VOLA**: Realized volatility; **VRA**: Trading volume; **DVRA**: first difference ofTrading volume; **AAII**: American Association of Individual Investors index; **II**: American Investors Intelligence index; **SENTIX**: German equity sentiment index; R_{big}: return on the large-size stock portfolio; R_{mid}: return on mid-size stock portfolio; R_{small}: return on small-size stock portfolio.
AC (1) is the autocorrelation coefficient at one lag. **ADF** is Augmented Dickey-Fuller test statistic with maximum 52 lags.

Variable		Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Sum Sq. Dev.	AC (1)	ADF
Financial Market Indicators	***AVDC***	1.0876	0.4549	1.2329	6.0842	525.589***	167.2282	0.005	-28.3206***
	CEFD	6.1710	1.9384	0.5394	4.4652	111.5912***	3035.919	0.946***	-4.1802***
	MFI	55.0233	23.520	-0.0673	2.3014	17.06343***	446983.2	0.799***	-6.0015***
	PCV	1.3526	0.4580	1.1055	6.3486	542.7550***	169.5227	0.169***	-9.8230***
	PCO	1.1830	0.1956	0.2522	2.1609	32.30725***	30.90311	0.962***	-3.9491***
	RSI	49.2066	25.7137	-0.4768	1.8330	76.4642***	533584.7	0.872***	-7.9520***
	VOLA	1.0117	0.6030	2.6823	14.4282	5372.483***	293.8059	0.820***	-6.4611***
	VRA	1.0261	0.1729	0.9335	7.7472	877.1272***	24.1509	0.926***	-1.2628
	DVRA	0.000003	0.0663	0.4674	6.5852	462.1597***	3.5507	0.512***	-10.2222***
Survey Sentiment Index	***AAII***	0.1092	0.1933	-0.0893	2.7079	3.942019	30.1047	0.672***	-9.2572***
	II	0.1863	0.1353	-0.7417	3.5538	84.51907***	14.7866	0.939***	-5.9866***
	SENTIX	0.1125	0.1167	0.5343	2.8921	25.5730***	7.2258	0.849***	-6.3767***
Market Returns	R_{big}	0.0575	2.4710	-0.3221	6.2673	373.8274***	4933.496	-0.091***	-31.1141***
	R_{mid}	0.1399	2.4603	-0.4941	5.6379	267.4875***	4890.773	0.041	-27.2452***
	R_{small}	0.0393	2.1286	-0.5987	6.9675	578.9446***	3660.873	0.320***	-11.8891***

3.2.4. Weekly Investor sentiment proxies and equity returns

Before constructing the sentiment index, the relationship between the sentiment proxies and equity returns is analysed regressing the returns on the sentiment proxies following the Brown and Cliff (2004) approach to examine the effect of investor sentiment on market returns. The sentiment proxies and their one period lagged are both included in the regressions. The autocorrelation coefficients indicate that returns of large-size stock has first order autocorrelation and returns of small-size stock have up to third order autocorrelation. Returns of medium-size stock, however, do not have autocorrelation. Therefore one lag of return is included in the regression for large-size stock returns, and three lags of return are included in the regression for small-size stock returns. The estimation models are as follows:

$$\begin{aligned} R_{size} = \alpha_0 &+ \sum\nolimits_{i=0}^{2} \beta_{1,i} AVDC_{t-i} + \sum\nolimits_{i=0}^{2} \beta_{2,i} CEFD_{t-i} + \sum\nolimits_{i=0}^{2} \beta_{3,i} MFI_{t-i} \\ &+ \sum\nolimits_{i=0}^{2} \beta_{4,i} PCV_{t-i} + \sum\nolimits_{i=0}^{2} \beta_{5,i} PCO_{t-i} + \sum\nolimits_{i=0}^{2} \beta_{6,i} RSI_{t-i} \\ &+ \sum\nolimits_{i=0}^{2} \beta_{7,i} VOLA_{t-i} + \sum\nolimits_{i=0}^{2} \beta_{8,i} DVAR_{t-i} + \sum\nolimits_{j=1}^{n} \theta_i R_{size,t-j} + \varepsilon_t \end{aligned} \tag{3.6}$$

where *size* = *big*, *mid* or *sml*; $n = 1$for large stocks and$n = 3$for small stocks.

They are estimated using Ordinary Least Square (OLS) method. For all three estimates, Breusch-Godfrey Serial Correlation LM Tests (includes 52 lags) reject the null hypothesis of the residual not being autocorrelated. The autoregressive conditional heteroscedasticity (ARCH) tests (include 2 lags) also reveal that the null hypothesis of residuals to be homoscedastic is rejected for all three regressions. Where there is residual autocorrelation and/or heteroscedasticity, OLS estimators still give unbiased and consistent coefficient estimates as long as no lagged dependent variables, but the standard errors could be wrong and consequently mislead inferences made based on them. Newey and West (1987) develop a variance-covariance estimator that produces heteroscedasticity and autocorrelation consistent (HAC) standard errors which correct for both heteroscedasticity and autocorrelation. The models are therefore estimated by

OLS with Newey-West HAC Standard Errors & Covariance, and the results are reported in Table 3.2.

For the large stocks, the weekly returns that are negative and statistically significant relate to $CEFD_{t-1}$, PCV_t, RSI_{t-1} and $VOLA_t$ but those that are positive relate to $AVDC_t$, $CEFD_t$, MFI_t, RSI_t, and $VOLA_{t-1}$. The coefficients of $AVDC_{t-1}MFI_{t-1}$, PCO_t, PCO_{t-1}, $PCV_{t-1}DVRA_t$, and $DVRA_{t-1}$ are statistically insignificant at the 10% level, indicating that the factors do not affect large stocks returns, which in general confirms that which is suggested from the correlation tests. For the small stocks portfolio, the coefficient of $AVDC_t$, $CEFD_{t-1}$, MFI_t, PCV_{t-1}, RSI_t, and $VOLA_{t-1}$ is positive, and that of $CEFD_t$ and $VOLA_t$ are negative and statistically significant. For the medium stocks portfolio, $AVDC_t$, $AVDC_{t-1}$, $CEFD_{t-1}$, MFI_t and $VOLA_{t-1}$ are statistically significant at the 10% level. More of the sentiment proxy variables seem to be able to predict future returns for large and small stocks. The variables with the most evidence of some ability to forecast future return are $AVDC$, $CEFD$ and $VOLA$. The regression for returns of medium-size stock shows that very few sentiment variables have predictive power as to the future returns.

Table 3.2: Weekly regressions of returns on sentiment proxies

Table 3.2 shows the results of estimating equations of the following form:

$$R_{size} = \alpha_0 + \sum_{i=0}^{1} \beta_{1,i} AVDC_{t-i} + \sum_{i=0}^{1} \beta_{2,i} CEFD_{t-i} + \sum_{i=0}^{1} \beta_{3,i} MFI_{t-i} + \sum_{i=0}^{1} \beta_{4,i} PCV_{t-i} + \sum_{i=0}^{1} \beta_{5,i} PCO_{t-i} + \sum_{i=0}^{1} \beta_{6,i} RSI_{t-i} + \sum_{i=0}^{1} \beta_{7,i} VOLA_{t-i} + \sum_{i=0}^{1} \beta_{8,i} DVAR_{t-i} + \sum_{i=1}^{n} \theta_i R_{size,t-i} + \varepsilon_t$$

As there is some evidence of autocorrelation, the estimation method is OLS with Newey-West standard errors.

Variable definitions:
size = *big*, *mid* or *sml*; so, $\boldsymbol{R_{big}}$: return on the large-size stock portfolio; $\boldsymbol{R_{mid}}$: return on mid-size stock portfolio; $\boldsymbol{R_{small}}$: return on small-size stock portfolio; **AVDC**: Advances to declines ratio; **CEFD**: Closed-end Fund Discount; **MFI**: Money Flow Index; **PCV**: Put-call volume ratio; **PCO**: Put-call open interest ratio; **RSI**: Relative Strength Index; **VOLA**: Realized volatility; **DVRA**: first difference ofTrading volume.
Adj-R^2: Adjusted R-squared; **S.E**: Standard Error of regression; **AIC**: Akaike information criterion.

	R_{big}		R_{mid}		R_{sml}	
Variable	**Coefficient**	**t-Statistic**	**Coefficient**	**t-Statistic**	**Coefficient**	**t-Statistic**
$AVDC_t$	3.4432***	12.9305	4.0788***	16.9843	2.7777***	13.1468
$AVDC_{t-1}$	-0.2444	1.0828	-0.3132*	1.9511	0.1219	0.7094
$CEFD_t$	0.8736***	5.9081	-0.1070	0.9711	-0.2897**	2.1221
$CEFD_{t-1}$	-0.7786***	5.7406	0.2463**	2.4225	0.4053***	3.0120
MFI_t	0.0077*	1.7532	0.0064*	1.7621	0.0086**	2.2920
MFI_{t-1}	-0.0043	0.9901	-0.0010	0.2871	-0.0041	1.1311
PCV_t	-0.4415**	2.5556	-0.0814	0.6431	0.0489	0.4187
PCV_{t-1}	-0.0902	0.5667	0.0950	1.0732	0.1808*	1.8086
PCO_t	1.5465	1.2046	0.3250	0.3455	0.4523	0.4743
PCO_{t-1}	-1.5666	1.2389	-1.3249	1.4625	-1.3547	1.5182
RSI_t	0.0067*	1.9095	0.0039	1.2023	0.0054*	1.9163
RSI_{t-1}	-0.0094***	2.7588	-0.0045	1.4008	-0.0050	1.5960
$VOLA_t$	-1.3277***	4.5117	-1.1671***	3.7928	-1.1919***	5.2281
$VOLA_{t-1}$	0.6463*	2.4199	0.3758	1.4999	0.6600***	2.9629
$DVRA_t$	0.0043	0.0037	-0.5206	0.5969	0.5249	0.6319
$DVRA_{t-1}$	1.3602	1.2422	1.6919	1.5365	0.9365	0.7730
Adj-R^2	0.6070		0.6945		0.5978	
S.E	1.5504		1.3612		1.3522	
F-Statistic	74.2508		115.5267		63.9601	
AIC	3.7370		3.4755		3.4659	

3.3 Construction of the weekly sentiment index

It is arguable that the use of financial market proxies to measure investor sentiment can be economic and practically efficient, since the data are widely available from high to low frequencies, and they can be more accurate than those of survey data. However, financial market activities can be led by a combination of an asset's fundamental and its investor sentiment. It is still not very clear that when using the sentiment proxies to explain asset returns, whether the explanatory power of the proxy variables comes from the fundamental part or the sentiment part of the proxies. The reason that the financial market variables are able to be used as sentiment proxies is that they all contain the factor of investor sentiment. This suggests that the sentiment factor extracted from the proxy variables may be a more effective measurement for investor sentiment. Brown and Cliff (2004) use the Kalman filter method as well as principal component method to extract the common components of the sentiment proxies to build a US investor sentiment index from selected sentiment proxy variables. Similarly, Baker and Wurgler (2006) also construct a US investor sentiment index from six selected sentiment proxies.

Combining Brown and Cliff (2004) with Baker and Wurgler (2006), eight sentiment proxy variables are used for constructing UK market investor sentiment indexes. They are: Market strengthen indicator (AVDC), Closed-end fund discount (CEFD), Money Flow Index (MFI), Put-call open interest ratios (PCO), Put-call volume ratio (PCV), Relative Strength Index (RSI),Realized volatility (VOLA), and the first difference of Trading volume (DVRA). These variables come from equity, future and option markets, where participants vary from individual to institutional investors, therefore the sentiment extracted from the variables is more likely to reflect UK market investor sentiment.

The index is constructed following the Baker and Wurgler (2006) approach, first principal component method. The first step is to estimate the first principal component of the eight sentiment proxies and their lags. This gives the first-stage index ($Index$) with 16 loadings, which is:

$$
\begin{aligned}
Index_t = {} & 0.0332AVDC_t + 0.1069AVDC_{t-1} - 0.2836CEFD_t - 0.2608CEFD_{t-1} \\
& + 0.2900MFI_t + 0.2952MFI_{t-1} + 0.2548PCO_t + 0.2449PCO_{t-1} \\
& + 0.1240PCV_t + 0.0975PCV_{t-1} + 0.3421RSI_t + 0.3379RSI_{t-1} \\
& - 0.3648VOLA_t - 0.3809VOLA_{t-1} - 0.0657DVRA_t \\
& - 0.0659DVRA_{t-1}
\end{aligned}
$$

The second step is to compute the correlation between the $Index$ and the current and lagged values of each of the proxies. In each pair of the lead and lag variables, whichever has higher correlation with the $Index$ will be used in next stage. The final step is to define the sentiment ($SENT$) as the first principal component of the correlation matrix of eight variables selected in the second step. This produces an index:

$$
\begin{aligned}
SENT_t = {} & 0.2128AVDC_{t-1} - 0.3655CEFD_t + 0.4044MFI_{t-1} + 0.3273PCO_t \\
& + 0.2128PCV_t + 0.4737RSI_t - 0.5169VOLA_{t-1} - 0.1165DVRA_{t-1}
\end{aligned}
$$

The correlation between the 16-term $Index$ and the $SENT$ index is 0.98, indicating that little information is lost in dropping the eight terms with other time subscripts. The first principal component explains 32% of the sample variance suggesting that one factor captures much of the common variation.

The sentiment proxies related to derivatives trading activities are viewed as measures of institutional sentiment because institutional investors are more likely to be dominant in the derivatives markets (Brown and Cliff, 2004). Therefore, the variables of PCO, PCV, and $VOLA$ are used for constructing institutional sentiment index ($SENT^p$). Using the same method and procedure as for the market sentiment index, $SENT$, the institutional sentiment index is produced thus:

$$
SENT_t^p = 0.6492PCO_t + 0.5344PCV_t - 0.5412VOLA_{t-1}
$$

The first principal component explains 55% of the sample variance demonstrating that one factor captures much of the common variation. The correlation between the 6-term first-stage index and $SENT^p$ is 0.92, showing that little information is lost in dropping the three terms with other time subscripts.

The variables, PCO_t, PCV_t, and $VOLA_{t-1}$ are used in the construction of both market sentiment index, $SENT$, and institutional sentiment index, $SENT^p$. This may lead to a problem of overlapping. An alternative market sentiment index, $SENT^m$, was therefore constructed by excluding PCO, PCV, and $VOLA$:

$$SENT_t^m = 0.3742AVDC_{t-1} - 0.2743CEFD_t + 0.5682MFI_{t-1} + 0.6443RSI_t - 0.2163DVRA_{t-1}$$

In this case, the first principal component explains 37% of the sample variance, implying that the common variation captured by the one factor has not changed much with PCO_t, PCV_t, and $VOLA_{t-1}$being excluded. This may suggest that $SENT_t^m$ captures the same factor as $SENT_t$. The correlation coefficient of $SENT_t^m$ and $SENT_t$ is 0.9997, and it is statistically significant at the 1% level, implying they are the two possible UK market sentiment indices. Therefore, the more comprehensive index, $SENT_t$, is used in the analysis.

$SENT$ and $SENT^p$ are plotted in Figure 3.1, and the statistical summaries of both variables are reported in Table 3.3 Panel A. The market sentiment index, $SENT$, displays positive autocorrelation; all the five autocorrelation coefficients are positive and statistically significant. The institutional sentiment index, $SENT^p$, exhibits a similar picture. These properties suggest that investors are more likely to be bullish if they were bullish in the previous period or bearish if they were bearish before, in other words, estimated sentiment is somewhat persistent.

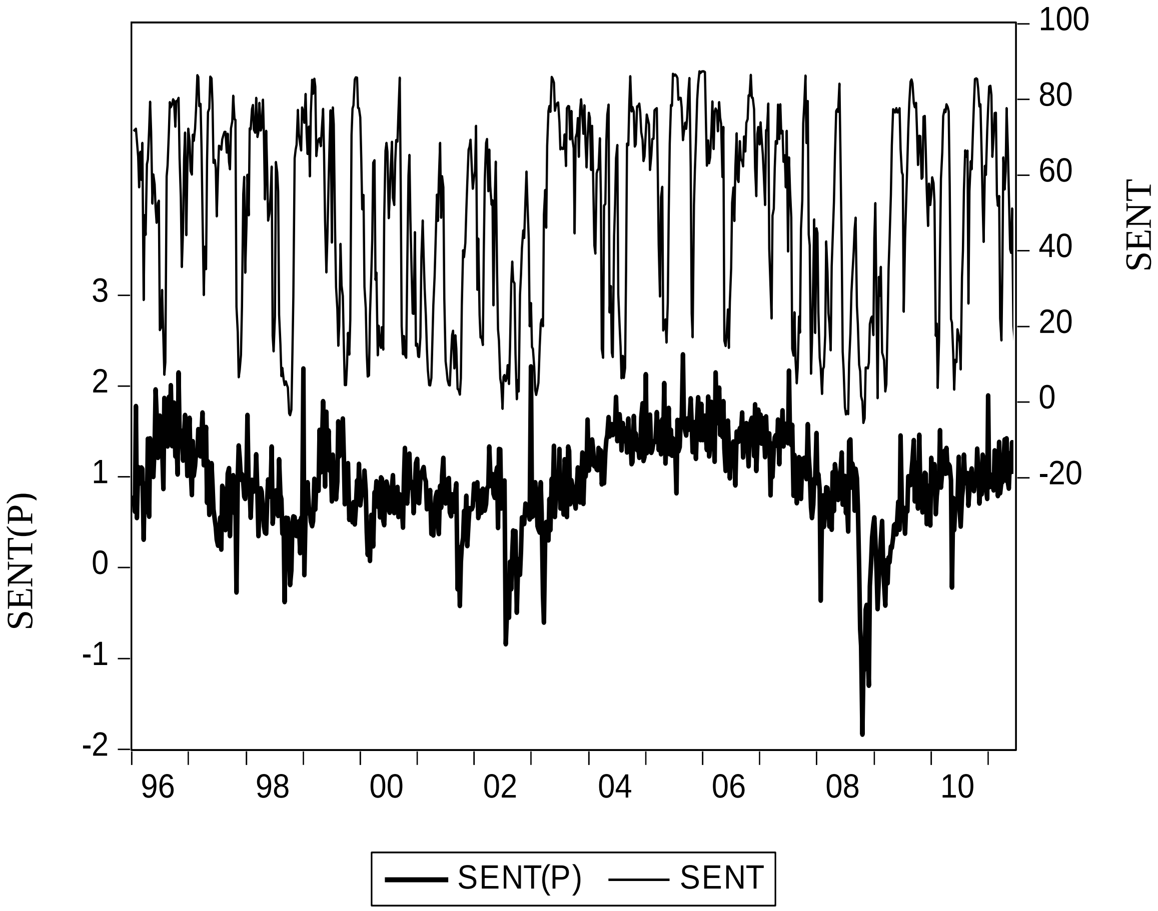


Figure 3.1: UK market investor sentiment index and institutional sentiment index, 1996 – 2011

Both indexes show that investors' sentiment was high in late 1996 and early 1997, the period before the Asian Financial Crisis. The market sentiment index, $SENT$, was still spiking high until late 1997, but the institutional sentiment index, $SENT^p$, falls down and stays below the mean until 1999 in the run up to the Dotcom bubble, then declines later in the period shortly before the bubble crash. The $SENT$is also high in early 1999, but it declines in the second half of the year. Both indexes stay high until mid 2007 when the global financial crisis started. However, the market sentiment, $SENT$, dips to bearish frequently, especially during 2004, the investors stay bearish for most of the year in contrast to the relative high level of $SENT^p$. These patterns may suggest that the two sentiment indices, $SENT$ and $SENT^P$, are both relatively persistent, but they are only moderately correlated with one another. They are likely to provide independent measures of investor sentiment. The patterns may also suggest that both market and institutional sentiment could have contributed to an asset price bubble.

Table 3.3 Panel B reports the correlation coefficients between *SENT* and $SENT^P$ and the component proxy variables. $SENT^P$ has high correlation with all its components, and also has strong correlation with several non-component indicators, notably *CEFD*. *CEFD* is normally thought of as an indicator for individual investor sentiment rather than institutional sentiment. The higher correlation between *CEFD* and $SENT^P$ than between *CEFD* and *SENT* may be attributable to the importance of institutions in the UK market (Ammer, 1990). Apart from *CEFD*, *SENT* has a higher correlation with the pure market sentiment indicators (ie. all except PCO_t, PCV_t, $VOLA_{t-1}$) than does $SENT^P$, and a lower correlation than $SENT^P$ with the institutional indicators: PCO_t, PCV_t, $VOLA_{t-1}$. This suggests that the components extracted for *SENT* and $SENT^P$ do capture sentiment from different groups of investors. Granger causality tests between *SENT* and $SENT^P$ (Table 3.3 Panel C) suggest that there is bi-directional causality and therefore no strong indication that either group of investors tends to lead market sentiment in the UK.

$SENT$ is considered to be a better measure of UK market wide investor sentiment than $SENT^P$, since it is extracted from variables that generally are seen as indicators of investor sentiment and used as proxies to measure investor sentiment. The first principle component of these variables is expected to be the factor that captures investor sentiment[16]. Similarly, $SENT^p$ is constructed to measure UK institutional sentiment by extracting the common component from the indicators that are used as proxies for institutional sentiment.

[16] A discussion of whether the constructed $SENT$ and $SENT^P$ are sentiment factors or common macroeconomic factors is discussed in section 3.9.2 by orthogonalising sentiment variables against key macroeconomic measures. Macroeconomic data is generally available in monthly or lower frequencies rather than weekly or higher frequencies. The examination is, therefore, conducted in the monthly frequency by using the Index of Production, available in monthly and lower frequencies, as the macroeconomic proxy. The Index of Production is a key component of gross domestic production measures which is more likely to reflect the business cycle rather than being confused with sentiment.

Table 3.3: Properties of weekly UK Investor Sentiment Indices

Panel A reports summary statistics of the constructed investor sentiment indexes: UK market sentiment (SENT) and UK institutional sentiment (SNETP)
Panel B shows pairwise correlation coefficients.
Panel C shows p-values for the F statistics from bilateral Granger causality tests

Variable definitions:
SENT: UK market sentiment; **SENT^{P}**: UK institutional sentiment; **AVDC**: Advances to declines ratio; **CEFD**: Closed-end Fund Discount; **MFI**: Money Flow Index; **PCV**: Put-call volume ratio; **PCO**: Put-call open interest ratio; **RSI**: Relative Strength Index; **VOLA**: Realized volatility; **DVRA**: first difference of Trading volume. **ADF** is the Augmented Dickey-Fuller test with a maximum of 52 lags.
***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

Panel A: Statistical summary of Weekly sentiment indices

Variable	Mean	Std Dev.	Skewness	Kurtosis	Jarque-Bera	ADF	Autocorrelations at lags 1-5				
							1	2	3	4	5
SENT	50.1432	26.1439	-0.4746	1.8324	76.1325***	-7.954***	0.872***	0.733***	0.595***	0.475***	0.356***
SENT^{P}	0.9436	0.5187	-0.8072	5.2046	251.3766***	-4.9581***	0.708***	0.686***	0.647***	0.632***	0.561***

Panel B: Investor sentiment correlation coefficients

	$SENT_t$	$SENT^{P}_t$	$AVDC_t$	$CEFD_t$	MFI_t	PCV_t	PCO_t	RSI_t	$VOLA_t$	$DVRA_t$
$AVDC_{t-1}$	0.3112***	0.0912***	0.0046	-0.0278	0.2697***	-0.0623*	0.0102	0.3619***	-0.0618*	-0.2099***
$CEFD_t$	-0.2595***	-0.4659***	0.0694**	1	-0.1056***	-0.1742***	-0.2576***	-0.2413***	-0.0658*	0.4667***
MFI_{t-1}	0.8014***	0.2961***	0.0052	-0.1413***	0.8003***	0.0822**	0.1323***	0.5903***	-0.1294***	-0.3166***
PCV_t	0.0564	0.6808***	-0.0834**	-0.1742***	-0.0437	1	0.3932***	0.0182	-0.1118***	-0.1055***
PCO_t	0.1540***	0.6835***	0.0002	-0.2576***	0.1158***	0.3932***	1	0.1227***	-0.2040***	-0.3827***
RSI_t	0.9550***	0.3600***	0.0290	-0.2413***	0.6262***	0.0182	0.1227***	1	-0.1433***	-0.4810***
$VOLA_{t-1}$	-0.5283***	-0.8123***	-0.0393	0.5093***	-0.3466***	-0.1788***	-0.4020***	-0.5106***	0.1594***	0.8201***
$DVRA_{t-1}$	-0.1391***	-0.0767**	-0.0068	-0.0176	-0.1166***	-0.0651	-0.0103	0.1159***	1	0.0584*
$SENT_t$	1	0.3967***								

Panel C: Granger causality tests of SENT

	SENT^{P}	
	SENT does not Granger Cause ***SENT^{P}***	***SENT^{P}*** does not Granger Cause ***SENT***
SENT	<0.0001	0.0072

3.4 UK investor sentiment and foreign investor sentiment

As financial markets are internationally integrated, investor sentiment may also be internationally correlated. Beckmann et al. (2011), Baker, Wurgler and Yuan (2012) and Bai (2014) discuss three channels through which investor sentiment contagion may occur. First, if investors in one country are optimistic (say) about investment prospects in another country, they may bid up the shares of that particular country. Second, if investors in one country are optimistic, this may cause a general shift into risky assets, including international equities. Both these channels postulate that the effect of foreign sentiment on home country share prices occurs through market purchases by foreign residents. Third, when foreign investors are optimistic about their own economy this leads to domestic investors being optimistic about the local economy due to the linkage between the two economies, the foreign sentiment affecting domestic share prices indirectly via domestic sentiment.

A fourth possible mechanism is argued that sentiment in a foreign country may affect sentiment in the home country directly because of the herding instinct of noise traders, and through this channel affect share prices, as home country residents become more or less optimistic and trade accordingly. It is well-established that "word-of-mouth" social interactions can affect sentiment and investment decisions (Shiller, 1984; Brown, Ivković, Smith and Weisbenner, 2008). Investors in different countries are not usually as geographically close to one another as the investors that Shiller and Brown *et al* investigated. However, internet message boards have a global reach and there is evidence that they influence sentiment and trading (Sabherwal, Sarkar and Zhang, 2011). Furthermore, foreign sentiment can become local where there is a relatively high proportion of foreign ownership of locally-listed stocks, as is the case in the UK. At end-2012, foreign investors owned 53.2% of the value of the UK stock market; of this, 48.3% was held by investors in North America[17]. Investing is a global business, and it seems plausible that (for example) US fund managers based in the UK might be as ready to listen to their US counterparts as well as to their British colleagues in London. Therefore, the hypothesis is that there may be direct contagion from sentiment in one country to sentiment in another, associated with an impact on share prices.

[17] Office of National Statistics, Ownership of UK quoted shares 2012. www.statistics.gov.uk.

Beckmann et al. (2011) use survey-based indices whereas Baker et al. (2012) and Bai (2014) used composed indices to examine cross-border contagion of investor sentiment. Contagion may be due to common (international) information used in forming sentiment in different countries, or equally to investors' herding across borders. However, a change of sentiment in one country may lead to a change in another country regardless of how sentiment is measured in different countries. The UK composed indices, $SENT$ and $SENT^p$, US survey- based indices, AAI and II, and German survey sentiment index, Sentix, are used to investigate the relationship between UK investor sentiment and US and German investor sentiment.

Sentix index is constructed by a German consulting firm, Sentix GmbH, based on their weekly survey started from February 2001. A typical survey has 740 institutional investors and about 2000 individual investors participate. The respondents are regarded as bullish, bearish or neutral according to their opinions on the financial markets for the short-term (next month) and the mid-term (next six months). For each market, indices are constructed by using the following formulation:

$$Sentix = \frac{\sum Bullish - \sum Bearish}{\sum All\ votes} \tag{3.7}$$

Since Sentix is only available from 28/02/2001, the analysis of the relation between UK investor sentiment and European investor sentiment is conducted for a period from 28/02/2001 to 30/06/2011.

As shown in Table 3.4 Panel A, both the $SENT^p$ and $SENT$ have stronger correlation with the US institutional sentiment than that with US individual sentiment. This may be because home investors, whether institutions or individuals, have less knowledge about foreign markets than home markets, and that they would be more likely to pay attention to foreign investment "experts", institutional investors' sentiment rather than to general foreign market sentiment. Particularly, in the case of $SENT^p$, the correlation coefficients show that UK institutional sentiment may have the least correlation to the US individual sentiment compared to the US institutional sentiment and the German institutional sentiment. The correlation coefficients of Sentix with $SENT$ and with $SENT^p$ are both about 30% and significant at the 1% level. This demonstrates that the UK-European sentiment correlation may be less than that of UK-US investor sentiment, which can be more than 55%.

The results of Granger-causality tests with 4 lags between the composed indexes and the US and German survey sentiment indexes are reported in Table 3.4 panel B. It presents significant evidence that the AAII, II, and Sentix Granger-cause $SENT$ and $SENT^p$; but the $SENT$ and $SENT^p$ do not Granger-cause AAII, II and Sentix. This suggests that the US and European investors' sentiment appears to lead UK investor sentiment, but not vice versa.

Table 3.4: Correlation and Granger causality tests: weekly UK and foreign investor sentiment

Panel A shows pairwise correlation coefficients among different sentiment indices.
Panel B shows p-values for the F statistics from bilateral Granger causality tests as between either of the UK indices (*SENT* or $SENT^P$) and any one of the US or German indices (*AAII*, *II*, or *SENTIX*)
Test 1: H_0: Granger-noncausality from the US/German index to the UK index.
Test 2: H_0: Granger-noncausality from the UK index to the US/German index.

Variable definitions:
SENT is UK market sentiment; $\mathbf{SENT^P}$ is UK institutional sentiment;
AAII is American Association of Individual Investors index; **II** is American Investors Intelligence index;
SENTIX is German equity sentiment index.
***Significant at 1% level; **Significant at 5% level; *Significant at 10% level.

Panel A: Correlation tests

	$SENT^P$	*SENT*	*AAII*	*II*	*SENTIX*
$SENT^P$	1.000000				
SENT	0.3967***	1.000000			
AAII	0.0850***	0.4113***	1.000000		
II	0.4352***	0.5554***	0.5066***	1.000000	
SENTIX	0.3006***	0.2983***	0.2467***	0.2588***	1.000000

Panel B: Granger causality tests

	AAII		II		SENTIX	
	Test 1	**Test 2**	**Test 1**	**Test 2**	**Test 1**	**Test 2**
SENT	<0.0001	0.9058	<0.0001	0.4826	0.3178	0.9598
$SENT^P$	<0.0001	0.3161	<0.0001	0.4701	0.0170	0.1207

The UK sentiment indices are further regressed on the US and German indices to investigate how far foreign investor sentiment directly affects UK investor sentiment. The basic model is:

$$SENT_t^K = \alpha_0 + \sum_{i=0}^{4} \gamma_i AAII_{t-i} + \sum_{i=0}^{4} \delta_i II_{t-i} + \sum_{i=0}^{4} \theta_i SENTIX_{t-i} + \sum_{i=1}^{4} \beta_i SENT_{t-i}^K + \varepsilon_t \quad (3.8)$$

where $SENT_t^K$ = UK market sentiment, or institutional sentiment (K=P).

The regression of UK sentiment, $SENT$ and $SENT^p$, on US and German sentiment indices is started by estimating the equation 3.8 using OLS method with Newey-West standard errors. The estimation results (Table 3.5) show that many of the higher order lagged term of variables are insignificant at the 10% level. The model therefore is amended by dropping some of these insignificant variables only where this did not produce unacceptable spikes in the estimated lag structure. A simplified regression model is estimated and the coefficient results for the simplified model are not much different from the basic model. Estimators AIC and Regression Standard Errors are improved in the simplified model, suggesting it is a better and more parsimonious model than the original model.

Turning first to the estimates including German sentiment, for UK market sentiment, one lagged period US individual and institutional sentiment and current European investor sentiment have some effect on UK market sentiment and the effect is positive. However, US individual sentiment in two periods ahead and US institutional sentiment in four periods ahead would have a negative impact on UK market sentiment. The opposite direction of the coefficients indicates a partial reversal of the effect of US investor sentiment. This may suggest a reverse effect of foreign investor sentiment to the UK investor sentiment. It can be seen that the one period lagged impact of AAII ($AAII_{t-1}$) is 20.0375 while the two-period lagged effect ($AAII_{t-2}$) is -15.5311, producing a much smaller total effect of 4.5064. Of course, the level of sentiment cannot easily be normalised on any particular metric, and so the exact magnitude of any specific coefficient does not have a precise interpretation.

For UK institutional sentiment, $SENT^p$, the estimated results show that current US individual and institutional have some positive effects on UK institutional sentiment. The negative and significant coefficient of one period lagged AAII confirms the reverse effect of foreign investor sentiment, particularly the US individual sentiment.

From the analysis above, it can be seen that in general, foreign investor sentiment has a broadly similar effect on UK market and institutional sentiment. However, by examining the details of the estimation results, a couple of differences can be observed. One is that the effects on UK market sentiment from US individual and institutional sentiment come from lagged terms of US investor sentiment rather than the current period, suggesting that US investor sentiment may have predictive power to UK market sentiment. The US investor effects on UK institutional sentiment, however, mainly come from the current period. This indicates that US investor sentiment is less likely to be able to predict UK institutional sentiment.

The other difference is that the reverse effect of US sentiment is absent from UK institutional sentiment. The estimated coefficients suggest that UK institutional sentiment is affected by current US institutional sentiment positively. This may be because, compared to individual investors, institutional investors have better knowledge and contact to their foreign peers. Moreover, many UK financial institutions, e.g. Goldman Sachs International Bank, JP Morgan Chase Bank, JP Morgan Securities Ltd, and Morgan Stanley Bank international, are subsidiaries of US based financial institutions, where formal and informal communications between employees in the subsidiaries and their headquarters may transfer sentiment. This internal information channel would lead to more rapid sentiment contagion than from external observation.

The main data period runs from January 1st 1996, but the $Sentix$ is only available from 28/02/2001, a shorter time-span than the US measures, the regressions are also run including only US sentiment for a longer time-span from 01/01/1996 to 30/06/2010. The basic model is:

$$SENT_t^K = \alpha_0 + \sum_{i=0}^{4} \gamma_i AAII_{t-i} + \sum_{i=0}^{4} \delta_i II_{t-i} + \sum_{i=1}^{4} \beta_i SENT_{t-i}^K + \varepsilon_t \tag{3.9}$$

Here, $SENT_t^K$ = UK market sentiment, or institutional sentiment (K=P).

As before, regressions are started by estimating the equation 3.9, and then, it is simplified by deleting some higher-order lagged terms that are insignificant. Estimated results (Table 3.5) show that AIC and the standard errors are lower in the simplified models, implying that the model is a more parsimonious representation of the data.

For UK market sentiment, the significance of current and lagged AAII coefficients demonstrate that US individual sentiment have a persistent impact on UK market sentiment. The signs of the coefficients again suggest the reverse effect, i.e. a reversal of the initial effect. The significance of lagged coefficients of II suggests that previous US institutional sentiment has an influence on UK market sentiment. Compared to US individual sentiment, the reverse effect of US institutional sentiment does not appear immediately after the initial period; instead, the reversal effect occurs after two periods' same direction effect. This may be because signals released from US 'experts' are less likely to be doubted immediately by UK investors. It takes longer time for the doubts to be confirmed.

For UK institutional sentiment, $SENT^p$, it can be seen that both US individual and institutional sentiment have explanatory power to UK institutional sentiment. The estimated coefficients suggest that US individual sentiment has a sustained impact on the UK institutional sentiment but US institutional sentiment has a short and immediate impact on the UK institutional sentiment. The coefficient hypotheses tests suggest that there is a possibility of the same degree but different directions of impact on UK institutional sentiment from US individual and institutional sentiment.

Looking at the regression results in UK market and institutional sentiment both variables are greatly influenced by US individual and institutional sentiment. For $SENT$, the impact of US individual sentiment is more likely to be immediate whereas the effect of US institutional sentiment takes longer to materialise. Both US individual and US institutional sentiment have an immediate impact on UK institutional sentiment, but US individual sentiment has more persistent effect on UK institutional sentiment than does US institutional sentiment.

In summary, UK institutional and market sentiment are both strongly and persistently affected by changes in foreign sentiment. Changes in US individual and institutional sentiment each have an immediate effect on both UK market and institutional sentiment. Both the signs and lag structures of these effects do however differ as between the US effects within each equation, and for the same variable across equations. There is strong evidence of an apparent partial reversal in the effect of foreign sentiment, perhaps reflecting second thoughts by home investors about changes in foreign sentiment. We can see that the sign reversals occur in all the foreign sentiment effects where the effect persists over more than a single week. Clearly, if the immediate impact of foreign sentiment changes is to induce UK investors to trade, then "second thoughts" may well induce trade reversals in the subsequent week(s), increasing UK stock market volatility as a result. German sentiment also has a significant contemporaneous and lagged effect on UK sentiment. When German sentiment is excluded from the model, the results for US sentiment are mostly qualitatively similar to those from the smaller sample, giving some confidence in the robustness of the qualitative results, especially bearing in mind the two different sample sizes.

Table 3.5: Regression analysis of weekly UK sentiment measures on foreign sentiment indexes

Table 3.5 reports the results of estimating equations of the general form:

$$SENT_t^K = \alpha_0 + \sum_{i=0}^{4} \gamma_i AAII_{t-i} + \sum_{i=0}^{4} \delta_i II_{t-i} + \sum_{i=0}^{4} \theta_i SENTIX_{t-i} + \sum_{i=1}^{4} \beta_i SENT_{t-i}^K + \varepsilon_t$$

The data are weekly and cover the period 1st January 1996 to 30th June 2011. Exceptionally the *SENTIX* index is available only from 28th February 2001. The estimation method is OLS with Newey-West standard errors.

Variable definitions:

$SENT^K$ = UK market sentiment (K=M), or institutional sentiment (K=P); **AAII**: American Association of Individual Investors index; **II**: American Investors Intelligence index; **SENTIX**: German equity sentiment index. t-statistics are shown in parentheses. ***Significant at 1% level; **Significant at 5% level; *Significant at 10% level.

	Including European sentiment 28/02/2001 - 30/06/2011				**Excluding European sentiment 01/01/1996 - 30/06/2011**			
	SENT		***$SENT^P$***		***SENT***		***$SENT^P$***	
	Model 1	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**
$AAII_t$	4.6676 (1.2944)	5.3684 (1.6286)	-0.4046*** (-4.1164)	–0.3753*** (-4.2692)	8.6421*** (2.6598)	7.5319** (2.3604)	-0.3150*** (-3.8414)	–0.2811*** (-3.7141)
$AAII_{t-1}$	20.0375*** (5.0724)	20.513*** (5.6241)	0.2996** (2.4329)	0.3556*** (3.3021)	17.5236*** (5.1657)	16.408*** (5.0958)	0.3230*** (3.4858)	0.3704*** (4.0184)
$AAII_{t-2}$	-15.5311*** (-3.6297)	–16.233*** (-4.0530)	0.1040 (0.8528)		-12.2858*** (-3.3648)	–13.896*** (-4.1477)	0.0347 (0.4044)	0.0523 (0.6224)
$AAII_{t-3}$	-4.5181 (-1.3298)		-0.1790 (-1.6249)		-5.1334 (-1.6063)		-0.1207 (-1.3101)	–0.1571* (-1.7043)
$AAII_{t-4}$	4.3235 (1.2180)		0.1274 (1.2747)		-0.6066 (-0.1847)		0.1405* (1.7137)	0.0648 (0.8513)
II_t	7.9060 (0.6486)	7.1304 (0.6174)	0.6749** (2.0557)	0.6440*** (2.8876)	11.0110 (1.0317)	12.9537 (1.2224)	0.5733** (2.1809)	0.5006*** (3.1315)
II_{t-1}	57.2529*** (3.9759)	53.078*** (3.7997)	0.1094 (0.2577)		47.9680*** (3.7696)	48.2156*** (3.8502)	0.0690 (0.1889)	
II_{t-2}	-25.5630 (-1.4139)	–18.744 (-1.0642)	0.6839 (1.4983)		-27.1570* (-1.7707)	–25.2721* (-1.6831)	0.3636 (0.9616)	
II_{t-3}	6.3183 (0.4273)	0.4475 (0.0303)	-0.7173 (-1.6367)		-5.1441 (-0.3863)	–6.5870 (-0.5107)	-0.3832 (-1.0350)	
II_{t-4}	-34.9410*** (-3.4789)	–35.655*** (-3.8218)	-0.2720 (-0.9777)		-17.8118** (-2.0613)	–24.2740*** (-3.0110)	-0.2542 (-1.1086)	
$SENTIX_t$	20.6476** (2.4592)	9.7933** (2.3710)	0.2037 (0.9043)	0.2509 (1.1993)				
$SENTIX_{t-1}$	-12.0741 (-1.1550)		0.2638 (0.9847)	0.3804 (1.5325)				
$SENTIX_{t-2}$	4.8635 (0.4200)		-0.8163*** (-2.9139)	–0.5728*** (-2.6287)				
$SENTIX_{t-3}$	0.4491 (0.0412)		0.4127 (1.4198)					
$SENTIX_{t-4}$	-8.0872 (-0.9031)		0.0037 (0.0159)					
$SENT_{t-1}$	0.8207*** (16.9068)	0.8121*** (32.176)			0.8464*** (23.0593)	0.8220*** (44.681)		
$SENT_{t-2}$	0.0209 (0.2882)				0.0165 (0.2973)			
$SENT_{t-3}$	-0.0061 (-0.0945)				-0.0274 (-0.5242)			
$SENT_{t-4}$	-0.0483 (-1.3165)				-0.0294 (-0.8261)			
$SENT^P_{t-1}$			0.3615*** (6.4897)	0.3656*** (6.8487)			0.3142*** (6.4092)	0.3182*** (6.4143)
$SENT^P_{t-2}$			0.2301*** (4.7134)	0.2199*** (4.7907)			0.2310*** (6.6229)	0.2301*** (6.5695)
$SENT^P_{t-3}$			0.1416*** (2.7764)	0.1289*** (2.5892)			0.1234*** (3.5792)	0.1154*** (3.2100)
$SENT^P_{t-4}$			0.0989* (1.9164)	0.0745 (1.4784)			0.1665*** (3.9962)	0.1488*** (3.4082)
Adj. R^2	0.8366	0.8362	0.7082	0.7011	0.8080	0.8078	0.6227	0.6209
S.E.	10.8932	10.867	0.3068	0.3076	11.4919	11.4846	0.3197	0.3204
AIC	7.6529	7.6298	0.5138	0.5010	7.7398	7.7323	0.5754	0.5752
LM test	1.5976***	0.9359	0.7174	0.8240	1.5078**	1.2494	1.1841	1.1633
ARCH	4.4172**	4.1401**	2.5251*	2.4847*	2.9918*	3.1165**	9.7366***	9.4315***

3.5 Investor sentiment effect on UK equity returns

In the section 3.2.4, the relationship between equity returns and investor sentiment have been analysed by regressing against the proxy variables. The results show that some of the proxies have highly statistically significant explanatory power over UK equity returns. However, it is difficult to be certain whether the explanatory power comes from the sentiment component of the proxies or the fundamental part of the proxy variables. Since $SENT$ and $SENT^p$ are extracted from the market sentiment proxies to measure investment sentiment, they are expected to be less likely to contain fundamental components. An analysis of the relationship between UK equity returns and $SENT$ and/or $SENT^p$ is more likely to reflect the real relationship of UK equity returns and investor sentiment.

The returns for large stock portfolio, R_{big}, medium stock portfolio, R_{mid}, and small stock portfolio, R_{sml}, are tested against the composed market sentiment index, $SENT$ and institutional sentiment index, $SENT^p$, as well as, the US individual sentiment index, $AAII$, and institutional sentiment index, II. Since Sentix is only available from 2001, the regressions do not include it in order to estimate under the full sample period data.

First, correlation tests have been conducted and the results are shown in Table 3.6 Panel A. The large stock returns display statistically significant correlation with US investor sentiment but it does not have a significant correlation with the two composed UK sentiment indexes. Returns of medium size stocks also display statistically significant correlation with the US individual and institutional sentiment. Additionally, it has statistically significant correlation to the UK market sentiment. Returns of small-stock portfolio exhibit the strongest correlation to the US individual and institutional sentiment. They also have a relatively high correlation to the UK market sentiment, though rather less so to the UK institutional sentiment. Among the different size stocks, it appears that the returns of small stocks have the strongest correlation to the US and the UK investor sentiment, and the large stocks are the group of stocks that have the weakest correlation to investor sentiment.

Table 3.6: Correlation and Granger causality test for weekly stock returns and investor sentiment

Panel A shows pairwise correlation coefficients between sentiment indices and different size UK stock portfolios. Panel B gives p-values for the F statistics from bilateral Granger causality tests as between the sentiment indices and the returns on different size UK stock portfolios.
Test 1: H_0: Granger-noncausality from stock returns to the sentiment index.
Test 2: H_0: Granger-noncausality from sentiment index to stock returns.

Variable definitions:

SENT: UK market sentiment; **SENT^P**: UK institutional sentiment; **AAII**: American Association of Individual Investors index; **II**: American Investors Intelligence index; **SENTIX**: German equity sentiment index.***R_{big}***: return on the large-size stock portfolio; ***R_{mid}***: return on mid-size stock portfolio; ***R_{small}***: return on small-size stock portfolio.The data are weekly and cover the period 1st January 1996 to 30th June 2011. Exceptionally the SENTIX index is available only from 28th February 2001.
***Significant at 1% level; **Significant at 5% level; *Significant at 10% level.

Panel A: Correlation tests			
	R_{big}	R_{mid}	R_{sml}
SENT	-0.0094	0.0917***	0.2563***
SENT^P	-0.0511	0.0015	0.0635*
AAII	0.2059***	0.2629***	0.3403***
II	0.1191***	0.2020***	0.2771***

Panel B: Granger causality tests						
	R_{big}		R_{mid}		R_{sml}	
	Test 1	**Test 2**	**Test 1**	**Test 2**	**Test 1**	**Test 2**
SENT	<0.0001	0.8899	<0.0001	0.7713	<0.0001	0.8345
SENT^P	<0.0001	0.8747	<0.0001	0.4804	<0.0001	0.4306
AAII	<0.0001	0.6950	<0.0001	0.4628	<0.0001	0.2980
II	0.0001	<0.0001	0.0001	<0.0001	0.0167	<0.0001

Second, Granger causality tests are conducted between returns and investor sentiment indexes (Table 3.6Panel B). It shows that $SENT$, $SENT^p$, and $AAII$, do not Granger-cause UK stock returns among all size of stocks. US institutional sentiment (II), on the other hand, does significantly Granger-cause returns of all sizes of UK stocks, implying that the US institutional sentiment does lead the UK stock price changes regardless of the size of stocks. The null hypotheses of Granger-noncausality from stock returns to the sentiment indexes are all rejected at the 5% level, suggesting that the UK market returns do Granger-cause UK and US investor sentiment. This reveals a very similar picture to the Brown and Cliff (2004) investigation of US equity return and investor sentiment, which suggests that market returns and sentiment may act as a system. In the study, they found strong evidence of market returns predicting investor sentiment, and very weak evidence of investor sentiment predicting stock returns over short horizons.

Discussion in Section 2.4suggests that psychological bias leads to noise traders' misperceptions that in turn cause asset price fluctuations (DeLong, et al 1990; Daniel et al, 1998; and Odean, 1998). Overconfident investors overreact to private information and drive stock prices away from fundamentals, and confidence will be affected by feedback from the outcome. Therefore, hypothesize is raised as that investor sentiment may have an immediate effect on stock returns, and stock returns may affect sentiment by the feedback effect. Brown and Cliff (2004) and Wang et al. (2006) show this feedback effect of stock returns in a VAR frame work. Granger causality also provides one test of this hypothesis.

A more general model of the impact of investor sentiment on UK stock returns is therefore to be considered. The analysis is begun by regressing UK equity returns on the two UK sentiment indexes, $SENT$and $SENT^p$, the model (model 1) is:

$$R_t = \alpha_0 + \sum_{j=1}^{4} \alpha_j R_{t-j} + \sum_{i=0}^{4} \beta_i SENT_{t-i} + \sum_{i=0}^{4} \gamma_i SENT_{t-i}^{p} + \varepsilon_t \quad (3.10)$$

whereR_t are the stock returns for either R_{big}, R_{mid}, or R_{sml}.

The estimation of model 1 results (Table 3.7) show that some of the lagged terms of variables are insignificant, therefore leading to an amended model (model 2) which drops some of the higher order lagged terms of variables. The estimation results of model 2 show that Adjusted R-square, standard deviation and Akaike Information Criterion (AIC) are improved in model 2 which suggests that model 2 is a more parsimonious representation of the data.

For returns of large stocks, the estimated coefficients show that both current and one lagged UK market sentiment have an effect on returns of UK large stocks. Values of the coefficients imply that current market sentiment has a positive effect and the one lagged market sentiment has a negative effect.

Table 3.7: Regression of weekly returns on UK sentiment indexes

Table 3.7 reports the results of regressions of the following general form:

$$R_{size,t} = \alpha_0 + \sum_{j=1}^{4} \alpha_j R_{size,t-j} + \sum_{i=0}^{4} \beta_i SENT_{t-i} + \sum_{i=0}^{4} \gamma_i SENT_{t-i}^{p} + \varepsilon_t$$

The data are weekly and cover the period 1st January 1996 to 30th June 2011. Exceptionally the *SENTIX* index is available only from 28th February 2001. The estimation method is OLS with Newey-West standard errors.

Variable definitions:

size = *big*, *mid* or *sml*; so, R_{big}: return on the large-size stock portfolio; R_{mid}: return on mid-size stock portfolio; R_{small}: return on small-size stock portfolio; **SENT**: UK market sentiment; $\mathbf{SENT^P}$: UK institutional sentiment.

$\bar{\mathbf{R}}^2$: the Adjusted R-squared; **S.E**:Standard Error of regression; **AIC**: Akaike information criterion; LM: Breusch/Godfrey LM test for residual autocorrelation; **ARCH**: ARCH test for Heteroskadasticity.

***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

	R_{big}		R_{mid}		R_{sml}	
	Model 1	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**
α_0	-0.1460 (-0.4535)	-0.1329 (-0.4055)	-0.0477 (-0.1401)	-0.1109 (-0.3029)	-0.2354 (-0.7261)	-0.3897 (-1.1355)
R_{t-1}	-0.1578** (-2.1356)	-0.1620*** (-2.0951)	0.0020 (0.0319)		0.2266*** (3.9998)	0.2378*** (4.0842)
R_{t-2}	-0.0398 (-0.6148)	-0.0519 (-1.0510)	0.0152 (0.2564)		0.0731 (1.5959)	
R_{t-3}	-0.0079 (-0.0986)	-0.0253 (-0.5036)	0.0518 (0.9209)		0.1115 (1.3319)	
R_{t-4}	-0.0983* (-1.6987)	-0.0856* (-1.7942)	-0.0237 (-0.4549)		-0.0803 (-1.5515)	
$SENT_t$	0.0228** (2.2538)	0.0234** (2.2361)	0.0130 (1.4312)	0.0135** (1.9907)	0.0199*** (2.9707)	0.0205*** (3.0320)
$SENT_{t-1}$	-0.0153 (-1.2682)	-0.0152* (-1.6779)	-0.0081 (-0.7223)	-0.0040 (-0.6409)	-0.0140 (-1.6447)	-0.0084 (-1.5366)
$SENT_{t-2}$	-0.0015 (-0.1350)		0.0023 (0.2022)		-0.0015 (-0.1618)	
$SENT_{t-3}$	0.0077 (0.6686)		0.0063 (0.6614)		0.0057 (0.7105)	
$SENT_{t-4}$	-0.0070 (-0.9213)		-0.0060 (-0.9225)		-0.0007 (-0.1273)	
$SENT^P{}_t$	-0.4171 (-0.8691)	-0.2932 (-0.7840)	-0.1301 (-0.3121)	-0.0767 (-0.2104)	-0.2542 (-0.9057)	-0.1804 (-0.7139)
$SENT^P{}_{t-1}$	-0.0337 (-0.0732)	0.0777 (0.2171)	0.1978 (0.5977)	0.2722 (0.9230)	0.3672 (1.5797)	0.4297* (1.8673)
$SENT^P{}_{t-2}$	0.0196 (0.0644)		-0.4936* (-1.6648)	-0.4350 (-1.4661)	-0.4176* (-1.8346)	-0.4485* (-1.9110)
$SENT^P{}_{t-3}$	0.2675 (0.7288)		0.2654 (0.8887)		0.1226 (0.5067)	
$SENT^P{}_{t-4}$	0.0372 (0.1155)		-0.0479 (-0.1319)		-0.0490 (-0.2022)	
Adj. R^2	0.0080	0.0129	-0.0001	0.0077	0.1273	0.1208
S.E.	2.4687	2.4598	2.4687	2.4548	1.9950	1.9991
AIC	4.6638	4.6492	4.6638	4.6414	4.2377	4.2319
LM	1.1434	1.0819	1.7338***	1.6281***	1.4532**	1.6552***
ARCH	56.0206***	55.0853***	49.1399***	55.0461***	23.8765***	39.9187***

For medium stock, the estimated coefficients show that current $SENT$ is statistically significant, and other sentiment variable coefficients are insignificant, demonstrating that returns of UK medium stocks are influenced by current UK market sentiment. However, the estimated $SENT_0$ is 0.013. This may be interpreted as that the impact that UK market sentiment has on returns of medium stocks is very small, sometimes can be as little as the insignificant UK institutional sentiment.

For returns of UK small stocks, the estimated results show that the sentiment factors that affect UK small stock returns are current UK market sentiment, one lagged and two lagged UK institutional sentiment.

Regressions of returns on the US and UK sentiment indexes are conducted to allow the examination in more detail of investor sentiment's ability to explain future returns. The general regression model is started:

$$R_t = \alpha_0 + \sum_{j=1}^{4} \alpha_j R_{t-j} + \sum_{i=0}^{4} \beta_i SENT_{t-i} + \sum_{i=0}^{4} \gamma_i SENT_{t-i}^{p} + \sum_{i=0}^{4} \delta_i AAII_{t-i} + \sum_{i=0}^{4} \theta_i II_{t-i} + \varepsilon_t \tag{3.11}$$

whereR_t are the stock returns for either R_{big}, R_{mid}, or R_{sml}.

The regression processes, again, start from estimating the basic model (results are in Table 3.8A) and then amending the models by dropping those variables that are insignificance at the 10% statistic level. The estimation results are displayed in Table 3.8B.

For large stocks(Table 3.8B), $AAII_0$ and $AAII_1$ are statistically significant at the 1% level, demonstrating that current period and one lagged term of US individual sentiment have the ability to explain the UK large size stocks' returns. Moreover, II_0, II_1, and II_4 are significant at the 5% level, implying that returns of UK large stocks are influenced by current, one lagged period, and four lagged period US institutional sentiment.

Regressions of returns of UK medium stocks (Table 3.8B) are quite similar to those of UK large stock returns. Current and one lagged terms of US individual sentiment together with current and two lagged terms of US institutional sentiment influence returns of UK medium stocks. US institutional sentiment has a slightly longer effect on medium size stock returns than that US individual sentiment has.

Regressions of returns of UK small stocks are reported (Table 3.8B). The coefficients of current and all three lagged AAII are significant, suggesting that US individual sentiment has a longer effect on returns of UK small stocks than that of returns of UK large and medium sizes stocks. The significance of current and two lagged term II also demonstrates that US institutional sentiment has an impact on UK small stock returns.

The regressions of return of the three sizes of stock portfolio all have statistically insignificant coefficients for the UK sentiment variables, $SENT$ and $SENT^p$. This implies that neither UK market sentiment nor UK institutional sentiment has an impact on returns of UK equities. It is quite different from the regression results presented in the previous section where the returns are regressed on UK sentiment indexes alone. The regressions show that UK market sentiment does influence UK stock returns, and UK institutional sentiment has an impact on returns of UK small stocks. In order to explain the differences, it is necessary to look back to the relationship between UK investor sentiment and US investor sentiment. From the analysis of the relationship between UK investor sentiment, $SENT$ and $SENT^p$, and US investor sentiment, it can be seen that both UK market sentiment and UK institutional sentiment are strongly influenced by US individual and institutional sentiment, but not vice versa. This suggests that the effect that UK investor sentiment has on returns of UK stocks is more likely to be run by US investor sentiment, i.e. UK investor sentiment influences on UK stock returns are 'made in the US'. One explanation may be the unusual proportion of UK company shares held by foreign investors, especially in the North America. According to the Office for National Statistics, by the end of 2010, foreign investors owned 41.2% of the value of the UK stock market with around 60% of these investors being North American[18]. The regressions of the three sizes of stock portfolios also show that US institutional sentiment in general has a greater impact than US individual sentiment on returns of UK stocks.

[18] Source from: Share Ownership: Ownership of UK quoted shares 2010, www.statistics.gov.uk

Table 3.8A: Regression of returns on weekly UK & US sentiment indexes

Table 3.8A reports the results of regressions of the following general form:

$$R_{size,t} = \alpha_0 + \sum_{j=1}^{4} \alpha_j R_{size,t-j} + \sum_{i=0}^{4} \beta_i SENT_{t-i} + \sum_{i=0}^{4} \gamma_i SENT_{t-i}^{p} + \sum_{i=0}^{4} \delta_i AAII_{t-i} + \sum_{i=0}^{4} \theta_i II_{t-i} + \varepsilon_t$$

The data are weekly and cover the period 1st January 1996 to 30th June 2011. The estimation method is OLS with Newey-West standard errors.

Variable definitions:

size = *big*, *mid* or *sml*; so, $\boldsymbol{R_{big}}$: return on the large-size stock portfolio; $\boldsymbol{R_{mid}}$: return on mid-size stock portfolio; $\boldsymbol{R_{small}}$: return on small-size stock portfolio; **SENT**: UK market sentiment; $\mathbf{SENT^P}$: UK institutional sentiment.

$\bar{\mathbf{R}}^2$: the Adjusted R-squared; **S.E**:Standard Error of regression; **AIC**: Akaike information criterion; LM: Breusch/Godfrey LM test for residual autocorrelation; **ARCH**: ARCH test for Heteroskadasticity. ***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

	R_{big}		R_{mid}		R_{sml}	
	Coefficient	**t-Statistic**	**Coefficient**	**t-Statistic**	**Coefficient**	**t-Statistic**
α_0	-0.4861*	-1.7483	-0.2680	-0.8307	-0.3269	-1.0550
R_{t-1}	-0.2580***	-3.8904	-0.0889	-1.5735	0.1700***	3.3080
R_{t-2}	-0.1051*	-1.7826	0.0094	0.1679	0.0985**	2.2367
R_{t-3}	-0.0945	-1.4123	0.0407	0.7581	0.1190	1.5126
R_{t-4}	-0.1170**	-2.2542	-0.0309	-0.6063	-0.0832*	-1.7370
$SENT_t$	0.0140	1.4917	0.0013	0.1479	0.0068	1.0788
$SENT_{t-1}$	-0.0079	-0.7483	-0.0011	-0.1109	-0.0044	-0.5727
$SENT_{t-2}$	-0.0005	-0.0519	-0.0004	-0.0360	-0.0043	-0.5021
$SENT_{t-3}$	0.0051	0.4795	0.0085	0.9526	0.0065	0.8783
$SENT_{t-4}$	-0.0061	-0.8482	-0.0070	-1.1181	-0.0009	-0.1682
$SENT^P_{t}$	-0.1513	-0.3507	0.0903	0.2440	-0.1052	-0.4183
$SENT^P_{t-1}$	-0.1137	-0.2627	0.0467	0.1440	0.2378	1.0314
$SENT^P_{t-2}$	0.1060	0.3995	-0.4160	-1.5569	-0.3616*	-1.6688
$SENT^P_{t-3}$	0.2290	0.7210	0.2488	0.9632	0.1540	0.7076
$SENT^P_{t-4}$	-0.0129	-0.0419	-0.1351	-0.3832	-0.0952	-0.4055
$AAII_t$	4.1735***	5.7801	4.2147***	5.5114	3.2172***	5.4291
$AAII_{t-1}$	-3.1631***	-4.7472	-3.0583***	-3.6814	-2.0632***	-3.0995
$AAII_{t-2}$	-0.4920	-0.6746	-1.1505	-1.5681	-1.3773**	-2.1733
$AAII_{t-3}$	0.6591	0.9347	1.2685	1.6341	1.2627*	1.8002
$AAII_{t-4}$	-0.5728	-0.7906	-0.6907	-0.9641	-0.2977	-0.5114
II_t	13.6056***	6.6048	11.9941***	6.2902	7.4225***	4.7399
II_{t-1}	-6.8929**	-2.0492	-3.7895	-1.2085	-0.2431	-0.1025
II_{t-2}	-1.7232	-0.6701	-5.7903*	-1.9134	-6.0093**	-2.1358
II_{t-3}	0.2849	0.1027	2.1089	0.6599	1.2281	0.4538
II_{t-4}	-3.9822**	-2.3114	-2.1234	-1.0679	-0.3269	-1.0550
Adj. R^2	0.1778		0.1575		0.2414	
S.E.	2.2513		2.2722		1.8657	
AIC	4.4917		4.5102		4.1160	
LM	1.2425		1.7112***		1.2199	
ARCH	52.6051***		47.0913***		16.5329***	

Table 3.8B: Regression of returns on weekly UK & US sentiment indexes after deleting insignificant variables

Table 3.8B reports the results of regressions of the following general form:

$$R_{size,t} = \alpha_0 + \sum_{j=1}^{4} \alpha_j R_{size,t-j} + \sum_{i=0}^{4} \beta_i SENT_{t-i} + \sum_{i=0}^{4} \gamma_i SENT_{t-i}^{p} + \sum_{i=0}^{4} \delta_i AAII_{t-i} + \sum_{i=0}^{4} \theta_i II_{t-i} + \varepsilon_t$$

The data are weekly and cover the period 1st January 1996 to 30th June 2011. The estimation method is OLS with Newey-West standard errors. Insignificant variables were deleted from the model only where this did not produce unacceptable spikes in the estimated lag structure.

Variable definitions:

size = *big*, *mid* or *sml*; so, R_{big}: return on the large-size stock portfolio; R_{mid}: return on mid-size stock portfolio; R_{small}: return on small-size stock portfolio; **SENT**: UK market sentiment; $\mathbf{SENT^P}$: UK institutional sentiment.

$\bar{R}^2$: the Adjusted R-squared; **S.E**:Standard Error of regression; **AIC**: Akaike information criterion; LM: Breusch/Godfrey LM test for residual autocorrelation; **ARCH**: ARCH test for Heteroskadasticity. ***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

	R_{big}		R_{mid}		R_{sml}	
	Coefficient	**t-Statistic**	**Coefficient**	**t-Statistic**	**Coefficient**	**t-Statistic**
α_0	-0.4475	-1.5391	-0.2855	-0.8792	-0.3225	-1.0527
R_{t-1}	-0.2322***	-4.3521			0.1740***	3.5123
R_{t-2}	-0.1153**	-2.5633			0.0979**	2.3197
R_{t-3}	-0.0971**	-2.3805			0.1078	1.5603
R_{t-4}	-0.1017**	-2.2285			-0.0765*	-1.8243
$SENT_t$	0.0064	1.2066	0.0008	0.2207	0.0036	0.9739
$SENT^P_t$	-0.0586	-0.2520	-0.1351	-0.5927	-0.0875	-0.3886
$SENT^P_{t-1}$					0.2257	1.0650
$SENT^P_{t-2}$					-0.3293	-1.5352
$AAII_t$	4.0103***	6.0382	3.8361***	5.1932	3.1935***	5.4831
$AAII_{t-1}$	-3.3533***	-5.7636	-3.1409***	-4.2974	-2.0525***	-3.2092
$AAII_{t-2}$					-1.4408**	-2.2948
$AAII_{t-3}$					1.1020*	1.8083
II_t	13.6888***	6.8353	11.8334***	6.2330	7.5338***	4.8302
II_{t-1}	-6.7411**	-2.0047	-4.1114	-1.2605	-0.1842	-0.0763
II_{t-2}	-1.8130	-0.7303	-5.3677**	-2.4268	-5.9423***	-2.9877
II_{t-3}	0.0155	0.0056				
II_{t-4}	-4.0696**	-2.5140				
Adj. R^2	0.1831		0.1564		0.2474	
S.E.	2.2388		2.2662		1.8560	
AIC	4.4670		4.4840		4.0945	
LM	1.3500*		1.7945***		1.1823	
ARCH	57.3004***		60.2359***		18.8388***	

3.6 Discussion of simultaneity problem

Many economic and/or financial variables can be interdependent. If regression models involve inter-dependent variables, OLS may be biased, leading to biased coefficient estimates and inconsistent estimators. The multivariate dynamic models which applied in previous sections' discussions have contained contemporaneous terms variables on the right hand of the equations. This may introduce simultaneity bias as the explanatory variable becomes endogenous.

The analysis of the relationship between return and investor sentiment in previous sections, for example, has used sentiment variables and their lagged terms as explanatory variable to vary sizes of asset returns. The models were estimated by applying OLS method. The coefficients may not be simultaneity biased and estimators would be consistent if the variables are not inter-dependent. However, empirical studies, such as Bandopadhyaya and Jones (2008), Wang, Keswani, and Taylor (2006), suggested that sentiment is Granger-caused by returns, which indicates that the regressions of Equation 3.10 may exhibit simultaneity bias. In order to avoid the simultaneity problem, the models (equation, 3.6, 3.10 and 3.11) are restructured by excluding the contemporaneous terms explanatory variables, and the regression results are reported in Appendix 3.

Comparing the estimated results (Table A1 and A2) to those of the models including the contemporaneous terms (Table 3.2 and 3.7), estimated coefficients of UK large stock returns exhibit significant differences, particularly in the regressions that investment sentiment was measured by using market indicators. Estimated coefficients of such as $CEFD_{t-1}$, RSI_{t-1} and $VOLA_{t-1}$ are significantly different. In the model with contemporaneous terms, they are statistically significant, implying that they have some explanatory power to returns of large stocks. In contrast, the estimations of the model without contemporaneous terms are statistically insignificant, suggesting that the variables do not have explanatory power to the returns of large stocks. The simultaneity problem which arose from the interdependence between UK investor sentiment and returns of UK large stocks may suggest that the estimated coefficients in Table 3.2 were biased, and the relationship revealed for the regression may not be correct. The relationship between returns of large stock and UK investor sentiment may need to be reinterpreted by amending the model to avoid the simultaneity problem. Estimated coefficients in Table A2 suggest that neither UK market sentiment nor UK institutional sentiment has explanatory power to returns of UK large stocks, which is consistent with the examination results of Wang, Keswani, and Taylor (2006). DeLong, et al (1990), Daniel et al (1998), and Odean (1998) suggest that psychological bias leads to noise traders' misperception causing the fluctuation of asset price. Overconfident investors overreact to private information and drive stock prices away from the fundamental, and the confidence will be affected by the feedback of the outcome. It, therefore, can be argued that investor sentiment may have an immediate effect on stock returns, and stock returns affect sentiment by the feedback effect. The estimates results of returns of large stocks in Table A1 – A2 may correspond to the feedback effect of return on investor sentiment.

The estimated results from the models which include US investor sentiment (Table A3 and Table 3.8A), on the other hand, reveal a slightly different story. The possible simultaneity problem in statistic estimations method does not affect the estimated coefficients of US institutional sentiment. Estimated II_{t-2} and II_{t-4} are statistically significant and have very similar values in both models.

The estimated parameters for medium and small sizes stocks, however, do not display the same differences as returns of large stocks. For example, the estimations suggested that UK institutional sentiment in two lagged terms has some explanatory powers to returns of UK medium and small stocks when US investor sentiment was not modelled in the equations, which agrees with the estimated outcomes of models including contemporaneous terms. This may be because the relationship of returns of UK medium and small stocks to investor sentiment is not interdependent, implying that the model containing contemporaneous terms does not have the simultaneity problem. The regressions by OLS, therefore, are likely to be unbiased and estimators to be consistent. Under such conditions, comparing the estimator from the two different kinds of models, the Adjusted R^2, regression Standard Deviation, and Akaike Information Criterion all suggest that the models with contemporaneous terms of sentiment variables are more parsimonious representations of the data.

Similar investigations have been conducted in the analysis of the effects of foreign investor sentiment on UK investor sentiment. Estimated coefficients in Table A4 are very similar to their corresponding values in Table 3.5, suggesting that contemporaneous terms variables of foreign sentiment may not give rise to the simultaneity problem, i.e. UK investor sentiment is not interdependent with foreign investor sentiment; instead, foreign investor sentiment, particularly, US investor sentiment has some explanatory power to UK investor sentiment. This relationship has also been revealed from the Granger Causality tests which show that $SENT$ and $SENT^P$ are Granger caused by AAII and II but not vice versa. Moreover, the Adjusted R^2, regression Standard Deviation, and Akaike Information Criterion all suggest that the models with contemporaneous terms of foreign sentiment variables are more parsimonious representations of the data than those without contemporaneous terms of foreign sentiment variables.

3.7 Investor sentiment and financial crisis

Previous analysis shows that the UK investors' sentiment has an effect on UK equity returns and the sentiment effect is 'made in the US'. In addition, it is thought that investor sentiment is more likely to influence investors' decision making during market extreme times, more precisely, financial or economic crisis time. The sample period of 1996-2011 has experienced several major economic and financial crises; therefore the sentiment effects in crisis time can be investigated. This is done by regressing the returns on $SENT$ and $SENT^p$ under three conditions: non-crisis period, pre-crisis periods, and in-crisis periods respectively.

Table 3.9: Crisis event period definition

Crisis	Pre-Crisis Period	Crisis Period
Asian Financial Crisis	17/10/1996-16/10/1997	17/10/1997-30/01/1998
Russian Financial Crisis	02/02/1998-20/07/1998	21/07/1998-29/01/1999
Dotcom bubble & crash	10/03/1999-09/03/2000	10/03/2000-09/03/2001
2007-8 Financial Crisis	19/07/2006-18/07/2007	19/07/2007-18/07/2008

The pre-crisis and crisis sample periods are detailed in Table 3.9. The event windows are generally defined as that from the defined crisis starting date, 1 year prior to this date is the pre-crisis period and 1 year after this date is the crisis period, but they can be of different lengths for individual events. The defined date of the beginning of each crisis is based mainly on the combination of the big events indicating the instability of financial markets and the effects starting to have a significant impact on the market price. Accordingly, the starting date of the Asian financial crisis is the 17th October 1997, when the new Taiwan dollar was forced to devalue and the Hong Kong dollar was attacked again. This led to the Hang Seng index falling 23% in three days and the FTSE350 price index falling nearly 10% in the following two weeks. The Russian financial crisis is identified as starting on 20th July 1998, when Russian monetary authorities raised the interest rate to over 100%. This is the same date that the FTSE350 reached its new high of 2972.3, but then fell nearly 25% over the following two and half months to 2239.1. The Dotcom bubble crash date is identified as 10th March 2000, when the technology-heavy NASDAQ Composite index reached its peak of 5048.62 and fell to less than 1500 which is more than a 70% fall over the next 2 years. The 2007-8 Global financial crisis starting date is set as 19th July 2007, when the Dow Jones Industrial Average closed above 14000 for the first time in its history and fell to less than 9000 (more than a 36%) over the following one and half years. The no-crisis periods is defined as all dates other than the pre-crisis and the in-crisis periods out.

Three dummy variables are included in the regression model to examine sentiment effect on return during different crisis times. The model is:

$$\begin{aligned} R_t = {} & \alpha_1^{no-cri} D_1 + \alpha_2^{no-cri} R_{t-1} * D_1 + \sum_{i=0}^{2} \beta_i^{no-cri} SENT_{t-i} * D_1 \\ & + \sum_{i=0}^{2} \gamma_i^{no-cri} SENT_{t-i}^{p} * D_1 + \alpha_1^{pre-cri} D_1 + \alpha_2^{pre-cri} R_{t-1} * D_2 \\ & + \sum_{i=0}^{2} \beta_i^{pre-cri} SENT_{t-i} * D_2 + \sum_{i=0}^{2} \gamma_i^{pre-cri} SENT_{t-i}^{p} * D_2 \\ & + \alpha_1^{in-cri} D_3 + \alpha_2^{in-cri} R_{t-1} * D_3 + \sum_{i=0}^{2} \beta_i^{in-cri} SENT_{t-i} * D_3 \\ & + \sum_{i=0}^{2} \gamma_i^{in-cri} SENT_{t-i}^{p} * D_3 + \varepsilon_t \end{aligned} \qquad (3.12)$$

Where R_t is return of the stock portfolio (either R_{big}, R_{mid}, or R_{sml}). $D_1 = 1$in non-crisis periods and zero otherwise; $D_2 = 1$ in pre-crisis periods and zero otherwise; $D_3 = 1$ for in-crisis periods and zero otherwise. The regression results are reported in Table 3.10.

For the large stock portfolio, estimated coefficients suggest that current institutional sentiment has an impact on returns during pre-crisis period but market sentiment may not. This implies that the asset prices bubble to some degree may be caused by investors' sentiment, particularly by institutional sentiment. The negative coefficient of $SENT_0^p$ in pre-crisis period suggests that high levels of optimism push current prices up, lowering subsequent returns. However, during non-crisis normal time, returns of large stocks are affected by two lagged terms of market sentiment. The positive value suggests that current investor optimism would lead to high returns in two weeks time.

Comparatively, the result of un-conditional regression indicates that returns of large stocks may be affected by current market sentiment. This displays quite a different picture from the results under the financial crisis condition.

For the medium-size stock portfolio, coefficients of sentiment variables are not significant at the 10% level in the result of unconditional regression, suggesting that returns of medium stock are likely not to be affected by investor sentiment. However, the two lagged of $SENT$ and current $SENT^p$are significant during the no-crisis period, demonstrating that institutional and market sentiment have an impact on returns in the normal time. The significance of current, one lagged and two lagged $SENT$ and one lagged of $SENT^p$ during pre-crisis periods suggests that both market and institutional sentiment have an impact on medium stock return during the bubble building period, and market sentiment has a long-term impact on returns.

For the small-size stock portfolio, coefficients show that both market and institutional sentiment have influence over returns of small stocks during normal time. The significance of current $SENT^p$ also suggests that the prices of small stocks are influenced by institutional sentiment in financial crisis time. The statistical insignificance of coefficients for sentiment variables during pre-crisis period implies that neither market sentiment nor institutional sentiment influences returns of small stocks in this period. The result of unconditional regression shows a very similar picture to the result from normal time, which is that both current market sentiment and post institutional sentiment have some explanatory power to returns of small stocks.

By examining the return and sentiment relation in different market conditions, it suggests during the normal period, equity prices are changed following investors' sentiment among all different sizes stocks. The prices of small size stock are affected by investor sentiment during the crisis period. For large and medium-size, UK equities traded are affected by the UK investor sentiment in the price bubble pre-crisis period, however, during the crisis period, equity prices are not affected by investor sentiment, which provides evidence to the general opinion that the asset prices bubble to some degree, is caused by investors' sentiment and the price crash can be interpreted as a process of the prices reversing back to their fundamentals. Evidence also shows that institutional sentiment plays a more important role than the individual sentiment in determining returns.

Table 3.10: Regression of weekly returns on UK sentiment indexes under financial crisis conditions

Table 3.10 reports the results of regressions of the following form:

$$R_{size,t} = \alpha_1^{no-cri} D_1 + \alpha_2^{no-cri} R_{size,t-1} * D_1 + \sum_{i=0}^{2} \beta_i^{no-cri} SENT_{t-i} * D_1 + \sum_{i=0}^{2} \gamma_i^{no-cri} SENT_{t-i}^{p} * D_1 + \alpha_1^{pre-cri} D_2 + \alpha_2^{pre-cri} R_{t-1} * D_2 + \sum_{i=0}^{2} \beta_i^{pre-cri} SENT_{t-i} * D_2 + \sum_{i=0}^{2} \gamma_i^{pre-cri} SENT_{t-i}^{P} * D_2 + \alpha_1^{in-cri} D_3 + \alpha_2^{in-cri} R_{t-1} * D_3 + \sum_{i=0}^{2} \beta_i^{in-cri} SENT_{t-i} * D_3 + \sum_{i=0}^{2} \gamma_i^{in-cri} SENT_{t-i}^{p} * D_3 + \varepsilon_t$$

The data are weekly and cover the period 1st January 1996 to 30th June 2011. The estimation method is OLS with Newey-West standard errors.

Variable definitions:

size = *big*, *mid* or *sml*; so, $\boldsymbol{R_{big}}$: return on the large-size stock portfolio; $\boldsymbol{R_{mid}}$: return on mid-size stock portfolio; $\boldsymbol{R_{small}}$: return on small-size stock portfolio; **SENT**: UK market sentiment; $\mathbf{SENT^P}$: UK institutional sentiment. $D_1 = 1$ in non-crisis periods and zero otherwise; $D_2 = 1$ in pre-crisis periods and zero otherwise; $D_3 = 1$ in in-crisis periods and zero otherwise. The pre- and in-crisis periods are as defined in Appendix 2. The no-crisis periods consist of the remaining observations in the sample. The total number of observation is 809: 183 weeks fall in pre-crisis period, 147 weeks are in-crisis and 479 weeks are normal.

T statistics are shown in parentheses.

***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

	R_{big}				R_{mid}				R_{sml}			
	Full period	**Normal period**	**pre-crisis period**	**in-crisis period**	**Full period**	**Normal period**	**pre-crisis period**	**in-crisis period**	**Full period**	**Normal period**	**pre-crisis period**	**in-crisis period**
α_1	0.1018 (0.3467)	-0.0918 (0.2482)	1.7738*** (3.2219)	1.1782 (1.3790)	-0.1246 (-0.3500)	-0.2892 (0.6369)	1.4424** (2.3399)	0.7117 (0.8129)	-0.3890 (-1.1194)	-0.5482 (1.1786)	0.9451 (1.5912)	0.3679 (0.5281)
R_{t-1}	-0.1418* (-1.9138)	-0.1228 (1.2993)	-0.1577** (1.9680)	-0.2925** (2.1323)	-0.0055 (-0.0885)	-0.0161 (0.2090)	0.2290** (2.4943)	-0.1325 (1.6151)	0.2379*** (4.0853)	0.1892** (2.4600)	0.3737*** (3.4853)	0.2879*** (3.4333)
$SENT_t$	0.0183* (1.8815)	0.0148 (1.1644)	0.0095 (0.6973)	0.0324 (1.5041)	0.0143 (1.6083)	0.0201* (1.6757)	-0.0232* (1.7826)	0.0156 (0.9537)	0.0204*** (2.9867)	0.0311*** (3.2240)	-0.0055 (0.5747)	0.0020 (0.1381)
$SENT_{t-1}$	-0.0169 (-1.5626)	-0.0229 (1.6053)	-0.0029 (0.1966)	-0.0227 (0.9496)	-0.0065 (-0.6108)	-0.0205 (1.4786)	0.0414** (2.5095)	-0.0049 (0.2098)	-0.0081 (-1.0300)	-0.0199** (1.9677)	0.0136 (1.2098)	0.0123 (0.6089)
$SENT_{t-2}$	0.0017 (0.2618)	0.0146* (1.6692)	-0.0160 (1.5282)	-0.0230 (1.6316)	0.0022 (0.3080)	0.0141 (1.5445)	-0.0230** (2.1772)	-0.0183 (1.0649)	-0.0003 (-0.7015)	0.0041 (0.5885)	-0.0090 (0.9634)	-0.0155 (1.1190)
$SENT^P_t$	-0.3531 (-0.9162)	-0.0857 (0.1650)	-0.9260** (2.2148)	-0.9462 (1.1341)	-0.0649 (-0.1818)	0.2254 (0.4543)	-0.5125 (1.2354)	-0.7694 (1.2070)	-0.1790 (-0.7015)	0.0561 (0.1640)	-0.4181 (1.1464)	-0.9314* (1.8576)
$SENT^P_{t-1}$	0.0113 (0.0281)	0.0262 (0.0515)	-0.1437 (0.3167)	-0.4246 (0.4236)	0.2754 (0.9341)	0.4773 (1.1717)	-0.8106* (1.7775)	-0.0048 (0.0082)	0.4290* (1.8609)	0.5732* (1.7441)	-0.3880 (1.2523)	0.2731 (0.5752
$SENT^P_{t-2}$	0.1391 (0.4432)	-0.1428 (0.3153)	0.3279 (0.7739)	0.1827 (0.3329)	-0.4587 (-0.9180)	-0.9180** (1.9791)	0.5483 (1.4453)	-0.2471 (0.5195)	-0.4452* (-0.7901)	-0.7901** (2.2030)	0.2191 (0.6760)	-0.2912 (1.2912)
F1	0.9203					0.1708	1.3727		0.6198	0.0054		3.4987*
F2		0.1201				4.0034**	2.2241		3.5303*	4.8884**		0.6862
F3							3.3725*		3.5376*	3.2096**		0.2980

Table 3.11: Regression of weekly returns on UK sentiment indexes under different market sentiment conditions

Table 3.11reports the results of regressions of the following general form:

$$R_{size,t} = \alpha_1^{high} D_1 + \alpha_2^{high} R_{size,t-1} * D_1 + \sum_{i=0}^{2} \beta_i^{high} SENT_{t-i} * D_1 + \sum_{i=0}^{2} \gamma_i^{high} SENT_{t-i}^{p} * D_1 + \alpha_1^{low} D_1 + \alpha_2^{low} R_{size,t-1} * D_2 + \sum_{i=0}^{2} \beta_i^{low} SENT_{t-i} * D_2 + \sum_{i=0}^{2} \gamma_i^{low} SENT_{t-i}^{p} * D_2 + \varepsilon_t$$

The data are weekly and cover the period 1st January 1996 to 30th June 2011. The estimation method is OLS with Newey-West standard errors.

Variable definitions:
size = *big*, *mid* or *sml*; so, $\boldsymbol{R_{big}}$: return on the large-size stock portfolio; $\boldsymbol{R_{mid}}$: return on mid-size stock portfolio; $\boldsymbol{R_{small}}$: return on small-size stock portfolio; **SENT**: UK market sentiment; $\mathbf{SENT^P}$: UK institutional sentiment. D_1 = 1 when $SENT_t > \overline{SENT}$ and zero otherwise; D_2 = 1 when $SENT_t < \overline{SENT}$ and zero otherwise.
Fi, i = 1,…,3, are F tests for the asymmetric effects of UK market sentiment and institutional sentiment: in different market conditions. F1: $\beta_0^{High} = \beta_0^{Low}$, where β_0^{High} is β_0 when $SENT_t > \overline{SENT}$ and β_0^{Low} is β_0 when $SENT_t < \overline{SENT}$. F2: $\beta_1^{High} = \beta_1^{Low}$, where β_1^{High} is β_1 when $SENT_t > \overline{SENT}$ and β_1^{Low} is β_1 when $SENT_t < \overline{SENT}$. F3: $\gamma_2^{High} = \gamma_2^{Low}$, where γ_2^{High} is γ_2 when $SENT_t > \overline{SENT}$ and γ_2^{Low} is γ_2 when $SENT_t < \overline{SENT}$.
***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

	R_{big}				R_{mid}				R_{sml}			
	$SENT_t > \overline{SENT}$		$SENT_t < \overline{SENT}$		$SENT_t > \overline{SENT}$		$SENT_t < \overline{SENT}$		$SENT_t > \overline{SENT}$		$SENT_t < \overline{SENT}$	
	Coef.	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**
α_0	0.1472	0.2204	0.1188	0.3115	0.2389	0.3457	-0.1635	0.3483	0.0881	0.1591	-0.5095	0.9801
R_{t-1}	-0.2272***	3.0123	-0.1065	1.0421	-0.1212	1.4419	0.0488	0.6354	0.1748*	1.8236	0.2623***	2.7158
$SENT_t$	0.0288**	2.1894	0.0124	0.6580	0.0208	1.3402	0.0096	0.5745	0.0212*	1.8084	0.0231	1.4938
$SENT_{t-1}$	-0.0292***	2.6762	-0.0089	0.5632	-0.0142	1.0270	-0.0006	0.0411	-0.0156	1.6162	-0.0028	0.2122
$SENT_{t-2}$	0.0047	0.6118	-0.0012	0.1225	0.0014	0.1739	0.0028	0.2504	0.0029	0.4549	-0.0034	0.3842
$SENT^P_t$	-0.5775	1.5870	-0.2502	0.3997	-0.3545	1.0887	0.0689	0.1222	-0.2650	1.1075	-0.2107	0.4862
$SENT^P_{t-1}$	-0.0112	0.0269	0.0736	0.1005	0.2868	1.0470	0.2626	0.4765	0.2417	1.1036	0.6011	1.5401
$SENT^P_{t-2}$	0.2973	1.0903	0.0086	0.0157	-0.3350	1.1942	-0.5450	1.0521	-0.3640*	1.6697	-0.5090	1.2648
F1	0.5357				0.2593				0.0098			
F2	1.1862											
F3									0.1013			

3.8 Weekly returns under different market sentiment condition

The above section illustrates that the influence that investor sentiment has on stock returns and institutional herding can be different during different stages of financial crisis. In this section, the impact that investor sentiment has on stock returns and investor herding is examined by investigating the possible asymmetric effect under different market sentiment conditions. The market wide sentiment is defined as high when the sentiment at time t is higher than its mean, i.e. $SENT_t > \overline{SENT}$, where $\overline{SENT}$ is the mean of the composed market sentiment. The market sentiment is defined as low when $SENT_t < \overline{SENT}$.

Firstly returns are regressed on the market sentiment, $SENT$, and the institutional sentiment, $SENT^p$ under high sentiment and low sentiment condition separately. From the regressions in Section 3.5, it can be seen that a model with two lagged terms of sentiment variables may be a more parsimonious model. The model therefore is as follows:

$$
\begin{aligned}
R_t = \alpha_1^{high} D_1 + \alpha_2^{high} R_{t-1} * D_1 + \sum_{i=0}^{2} \beta_i^{high} SENT_{t-i} * D_1 + \sum_{i=0}^{2} \gamma_i^{high} SENT_{t-i}^{p} * D_1 \\
+ \alpha_1^{low} D_1 + \alpha_2^{low} R_{t-1} * D_2 + \sum_{i=0}^{2} \beta_i^{low} SENT_{t-i} * D_2 \\
+ \sum_{i=0}^{2} \gamma_i^{low} SENT_{t-i}^{p} * D_2 + \varepsilon_t
\end{aligned}
\tag{3.13}
$$

where R_t is return of the stock portfolio (either R_{big}, R_{mid}, or R_{sml}). $D_1 = 1$ when $SENT_t > \overline{SENT}$ and zero otherwise; $D_2 = 1$ when $SENT_t < \overline{SENT}$ and zero otherwise. The regression results are reported in table3.11.

For large-size stocks, the estimated coefficients indicate that current and lagged market sentiment has influence on returns when market sentiment is high. Tests for asymmetric effect of market sentiment under different market sentiment conditions suggest that market investor sentiment has symmetrically effects on returns. All institutional sentiment variables are insignificant in both high and low market sentiment times, implying that institutional investor sentiment does not affect returns of large stocks regardless of the market sentiment situation.

The sentiment coefficients for medium-size stocks are insignificant at the 10% level, suggesting that investor sentiment has no impact on returns of medium stocks. Null hypothesis of asymmetrically effects of market sentiment is rejected suggesting a symmetrical effect of market sentiment on returns of medium stocks under different market sentiment conditions.

For small-size stocks, when market sentiment is high, coefficient of current market sentiment and two lagged institutional sentiment are significant, implying that market sentiment and institutional sentiment have some explanatory power on the returns of small stocks when the market wide sentiment is high. Coefficients of sentiment variables are insignificant when market wide sentiment is low, suggesting that neither market sentiment nor institutional has an effect on returns of small stocks when market wide sentiment is low. Similar to the large and medium stock, null hypothesis of asymmetrically effects of market and institutional sentiment are rejected suggesting a symmetrical effect of market and institutional sentiment on returns of small stocks under different market sentiment conditions.

The return regressions under high and low market sentiment conditions show that returns of all size stocks are not affected by investor sentiment when the overall market sentiment is low. However, when market sentiment is generally high, returns of stocks can be affected by investor sentiment depending on the size of the shares. Returns of large stocks are more likely to be influenced by market sentiment and returns of small stocks are influenced by both market and institutional sentiment.

The next step is to factor US sentiment factor into the analysis. The regression model is:

$$R_t = \alpha_1^{High} D_1 + \alpha_2^{High} R_{t-1} * D_1 + \sum_{i=0}^{2} \beta_i^{High} SENT_{t-i} * D_1 + \sum_{i=0}^{2} \gamma_i^{High} SENT_{t-i}^{p} * D_1 + \sum_{i=0}^{2} \delta_i^{High} AAII_{t-i} * D_1 + \sum_{i=0}^{2} \theta_i^{High} II_{t-i} * D_1 + \alpha_1^{Low} D_1 + \alpha_2^{Low} R_{t-1} * D_2 + \sum_{i=0}^{2} \beta_i^{Low} SENT_{t-i} * D_2 + \sum_{i=0}^{2} \gamma_i^{Low} SENT_{t-i}^{p} * D_2 + \sum_{i=0}^{2} \delta_i^{Low} AAII_{t-i} * D_2 + \sum_{i=0}^{2} \theta_i^{Low} II_{t-i} * D_2 + \varepsilon_t \quad (3.14)$$

whereR_t is return of the stock portfolio, R_{big}, R_{mid}, or R_{sml}. $D_1 = 1$when$SENT_t > \overline{SENT}$ and zero otherwise; $D_2 = 1$ when $SENT_t < \overline{SENT}$ and zero otherwise. The regression results are reported in Table 3.12.

For large stocks, estimated coefficients suggest that UK market sentiment, US individual and institutional sentiment all have impact on returns for more than one period when the market sentiment is high, especially US institutional sentiment, which has continued three period effects on returns of UK large stocks when market sentiment is high. The positive current period coefficients and negative lagged coefficients of sentiment variables indicate a reversal effect of investor sentiment. Tests of the coefficients $SENT_0^{high} = -SENT_1^{high}$ and $AAII_0^{high} = -AAII_1^{high}$ cannot be rejected at the 10% level, suggesting that the influences of UK market sentiment and US individual sentiment may be reversed in the following period. This may imply that UK market sentiment and US individual sentiment have a short impact on returns of UK large stocks, which reflects the reverse effect of investor sentiment. If the immediate impact of investor sentiment changes is to induce investors to trade, then “second thoughts” may well induce trade reversals in the subsequent week(s), increasing UK stock market volatility as a result.

The estimated coefficients, $AAII_0^{low}$, $AAII_1^{low}$, and II_0^{low}, are statistically significant demonstrating that current and one period lagged US individual sentiment and current US institutional sentiment affects returns of UK large stocks when general market sentiment is low. The hypothesis tests suggest reversal effect of sentiment from one period to the previous period is not to the same degree as that in the high market sentiment condition. This indicates that investor sentiment influence on equity returns is more persistent if the general market sentiment is low.

A further examination of asymmetric effects of investor sentiment shows that UK market sentiment and US individual sentiment affect returns of UK large stocks asymmetrically and US institutional sentiment influences returns of UK large stocks symmetrically. Null of $\mathrm{AAII}_0^{\mathrm{high}} = \mathrm{AAII}_0^{\mathrm{low}}$ and $\mathrm{AAII}_1^{\mathrm{high}} = \mathrm{AAII}_1^{\mathrm{low}}$ are rejected at the 10% significance levels, indicating an asymmetrical effect on returns from US individual investor sentiment, and the coefficients suggest that US individual sentiment has a stronger impact on return when market sentiment is low. The coefficient tests of null of $\mathrm{II}_0^{\mathrm{high}} = \mathrm{II}_0^{\mathrm{low}}$ and $\mathrm{II}_1^{\mathrm{high}} = \mathrm{II}_1^{\mathrm{low}}$ cannot be rejected at the 10% level, demonstrating a symmetrical effect on returns from US institutional sentiment.

Similar to large stocks, US individual sentiment and US institutional sentiment have some explanatory power to returns of UK equity when general market sentiment is high. The reversal effect on returns from US individual sentiment also exists. The different size effect US individual and institutional sentiment also appears in return of medium stocks. Moreover, only current US institutional sentiment is significant suggesting that the effect on returns from US institutional sentiment is more persistent. However, the coefficients of UK market sentiment are insignificant demonstrate UK investor sentiment does not affect UK medium stock returns when market sentiment is high. The sentiment effects of US and UK investor sentiment on returns of medium stocks in a low market sentiment period display a very similar picture as that in a high market sentiment period. Both US individual and institutional sentiment have impact on returns of UK medium equities, but UK market and institutional sentiment do not have explanation power to returns of medium stocks. The reversal effect of US institutional sentiment exists in the low sentiment market which is different from that of the large stocks. The examination of asymmetric effects of investor sentiment shows a similar result as to the large stock, which is that US individual sentiment affects returns of UK medium stocks asymmetrically and US institutional sentiment influence returns of UK medium stocks symmetrically.

Similar to large and medium stocks, US individual and institutional sentiment have impacts on returns of UK small stocks in both high and low market sentiment conditions. The reversal impact on returns of small stocks only exists in US institutional sentiment and the influence of US individual sentiment is more persistent when market sentiment is high. This is different from large and medium stocks which presents a reversal effect of US individual sentiment on returns under high market sentiment condition. When market sentiment is low, the reversal effect on return of small stocks exists in both US individual and institutional sentiment which is similar to that of medium stocks. The same as large and medium stocks, the asymmetric effect on returns of UK small stocks appears on US individual sentiment, as the null of $AAII_0^{high} = AAII_0^{low}$ is rejected at the 5% significance level. The return effect of US institutional sentiment is symmetrical in the high and low sentiment market.

Returns of three different sizes of UK equities are regressed again UK and US sentiment indices under different market sentiment condition. When US investor sentiment has not been taken into account, Estimated results suggest that returns of UK large and small stocks are affect by UK market sentiment, and UK institutional sentiment has impact on the return of small stocks when the market wide sentiment is high. However, the effect of UK market sentiment on return of small stocks is less significant than that on return of large stocks. Returns of all sizes of stocks are not affected by investor sentiment when market sentiment is low. When US investor sentiment is considered, the effect of UK market sentiment on return of large stocks exists along with effects of US individual and institutional sentiment when market wide sentiment is high. The UK market sentiment effect on return of small stock, however, is insignificant. The impact of investor sentiment for small stocks comes from US investor sentiment. This reflects the suggestion of UK investor sentiment ‘born in USA’. The examinations of impact UK and US investor sentiment on different sizes of UK stock return under different market sentiment conditional also suggest that US investor sentiment has impact on UK equity returns regardless the size and the market condition different. Generally, US individual sentiment has an asymmetrical effect on UK returns under different market sentiment conditions and US institutional sentiment has a symmetrical effect.

Table 3.12: Regression of weekly returns stocks on UK and US sentiment indexes under different market sentiment conditions

Table 3.12 reports the results of regressions of the following general form:

$$R_t = \alpha_1^{High} D_1 + \alpha_2^{High} R_{t-1} * D_1 + \sum_{i=0}^{2} \beta_i^{High} SENT_{t-i} * D_1 + \sum_{i=0}^{2} \gamma_i^{High} SENT_{t-i}^{p} * D_1 + \sum_{i=0}^{2} \delta_i^{High} AAII_{t-i} * D_1 + \sum_{i=0}^{2} \theta_i^{High} II_{t-i} * D_1 + \alpha_1^{Low} D_1 + \alpha_2^{Low} R_{t-1} * D_2 + \sum_{i=0}^{2} \beta_i^{Low} SENT_{t-i} * D_2 + \sum_{i=0}^{2} \gamma_i^{Low} SENT_{t-i}^{p} * D_2 + \sum_{i=0}^{2} \delta_i^{Low} AAII_{t-i} * D_2 + \sum_{i=0}^{2} \theta_i^{Low} II_{t-i} * D_2 + \varepsilon_t$$

The data are weekly and cover the period 1st January 1996 to 30th June 2011. The estimation method is OLS with Newey-West standard errors.

Variable definitions:

size = *big*, *mid* or *sml*; so, R_{big}: return on the large-size stock portfolio; R_{mid}: return on mid-size stock portfolio; R_{small}: return on small-size stock portfolio; **SENT**: UK market sentiment; $\mathbf{SENT^P}$: UK institutional sentiment. $D_1 = 1$ when $SENT_t > \overline{SENT}$ and zero otherwise; $D_2 = 1$ when $SENT_t < \overline{SENT}$ and zero otherwise.

Fi, i = 1,…,4, are F tests for the asymmetric effects of UK market sentiment and institutional sentiment: in different market conditions. F1 $\delta_0^{high} = \delta_0^{Low}$, where δ_0^{high} is δ_0 when $SENT_t > \overline{SENT}$ and δ_0^{Low} is δ_0 when $SENT_t < \overline{SENT}$. F2 $\delta_1^{high} = \delta_1^{low}$, where δ_0^{high} is δ_0 when $SENT_t > \overline{SENT}$ and δ_0^{low} is δ_0 when $SENT_t < \overline{SENT}$. F3 is f-statistic of null hypothesis of $\theta_0^{high} = \theta_0^{low}$, where θ_0^{high} is θ_0 when $SENT_t > \overline{SENT}$ and θ_0^{low} is θ_0 when $SENT_t < \overline{SENT}$. F4 is f-statistic of null hypothesis of $\theta_1^{high} = \theta_1^{low}$, where θ_1^{high} is θ_1 when $SENT_t > \overline{SENT}$ and θ_1^{low} is θ_1 when $SENT_t < \overline{SENT}$.

***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

	R_{big}		R_{mid}		R_{small}	
	$SENT_t > \overline{SENT}$	$SENT_t < \overline{SENT}$	$SENT_t > \overline{SENT}$	$SENT_t < \overline{SENT}$	$SENT_t > \overline{SENT}$	$SENT_t < \overline{SENT}$
α_0	-0.0357 (-0.0557)	-0.0956 (-0.3033)	-0.1400 (-0.2191)	-0.5041 (-1.2561)	-0.1011 (-0.1954)	-0.7088 (-1.5173)
R_{t-1}	-0.2939*** (-4.2377)	-0.1842** (-1.9823)	-0.1822** (-2.2789)	-0.0569 (-0.7514)	0.1504* (1.6541)	0.1942** (2.1518)
$SENT_t$	0.0262** (2.1741)	-0.0008 (-0.0453)	0.0129 (0.9202)	0.0000 (-0.0004)	0.0119 (1.0885)	0.0087 (0.6047)
$SENT_{t-1}$	-0.0265*** (-2.6471)	0.0017 (0.1174)	-0.0103 (-0.7884)	0.0090 (0.6080)	-0.0096 (-1.0514)	0.0107 (0.8311)
$SENT_{t-2}$	0.0050 (0.7191)	-0.0039 (-0.4231)	0.0018 (0.2288)	0.0007 (0.0669)	0.0038 (0.6213)	-0.0069 (-0.7807)
$SENT^P_t$	-0.4658 (-1.3693)	-0.2098 (-0.3539)	-0.1736 (-0.5548)	0.1769 (0.3713)	-0.1218 (-0.5319)	-0.1414 (-0.3914)
$SENT^P_{t-1}$	-0.0490 (-0.1218)	-0.2070 (-0.2964)	0.2498 (0.9036)	-0.0482 (-0.0915)	0.2090 (0.9367)	0.3886 (1.0140)
$SENT^P_{t-2}$	0.2757 (1.1245)	0.2266 (0.4777)	-0.3591 (-1.2772)	-0.4086 (-0.8818)	-0.3568 (-1.5779)	-0.4138 (-1.1220)
$AAII_t$	2.0035*** (3.0210)	7.0849*** (5.6178)	2.9546*** (3.6001)	5.7782*** (4.6780)	2.1272*** (3.4024)	4.4667*** (4.4174)
$AAII_{t-1}$	-2.1883*** (-2.9852)	-4.6128*** (-3.7900)	-1.6312* (-1.7963)	-4.7465*** (-3.3130)	-1.0472 (-1.5046)	-3.0301*** (-2.6676)
$AAII_{t-2}$	-0.2130 (-0.3207)	-0.4006 (-0.3346)	-0.6660 (-0.8102)	-0.8024 (-0.7774)	-0.5510 (-0.8920)	-0.7356 (-0.7816)
II_t	11.8238*** (5.7023)	13.5813*** (4.0469)	10.3684*** (4.3234)	12.5905*** (4.4647)	6.7238*** (3.6356)	6.5767*** (2.6505)
II_{t-1}	-6.7462** (-2.1545)	-7.0243 (-1.2315)	-4.6686 (-1.3290)	-2.1619 (-0.4154)	-1.9521 (-0.7281)	2.4268 (0.5699)
II_{t-2}	-4.2690** (-1.9798)	-4.4310 (-1.1804)	-3.9287 (-1.4940)	-7.2262** (-2.1916)	-4.0544* (-1.7781)	-6.6851** (-2.1241)
F1	12.6208***		3.8918**		4.0863**	
F2	3.0123*		3.7489*			
F3	0.2111		0.3710		0.0023	
F4	0.0019				0.4703	

3.9 Monthly Investor sentiment measures

In their study, Brown and Cliff (2004) constructed sentiment index based on US financial indicators in weekly and monthly frequencies, and suggest that investor sentiment is negatively related to small stock return in the monthly frequency, but in weekly frequency, institutional sentiment has some predictive power for large stock return. The weekly and monthly sentiment indices conducted in Brown and Cliff (2004) utilised different sample time spans which makes it difficult for a comparison of investor sentiment impact on returns in different investor intervals. Baker and Wurgler (2006) also constructed an investor sentiment index from US financial indicators in a monthly frequency, and it has been widely used as a sentiment measure in scholarly research. So far, the only constructed UK investor sentiment indices (to the author's knowledge) are Baker et al (2012) and Bai (2014) which has composed in one frequency[19]. Therefore, there is a gap for constructed UK monthly frequency sentiment measures. In the following sections a monthly UK investor sentiment is going to be constructed. The monthly index is constructed by using the same components in the same time span. This therefore, provides a better like for like comparison of investor sentiment effect on equity return in different time intervals.

Apart from the sentiment indicators discussed in weekly analysis, there are more sentiment measures available in monthly frequencies. This includes UK Consumer Confidence Index (CCI), the number of Initial Public Offerings (NIPO) and Fund cash flow (CFLW). Consumer Confidence Index is used as an indicator to measure the degree of optimism on the country's economy and consumers' personal financial situation, which is expressed through consumer's activities of savings and spending. The UK Consumer Confidence Index is conducted by the European Commission based on the monthly surveys of consumer confidence. The number of Initial Public Offerings is the number of new issues on the London Stock Exchange main market[20]. The fluctuations of IPO volumes can be interpreted by the investor sentiment (Baker & Wurgler, 2006). Fund cash flow is seen as an indicator of institutional sentiment since the proportion of fund assets held in cash reflects how optimistic the fund managers are about the market. CFLW in this study is an average of the percentage cash assets held

[19]Baker et al (2012) composed the index in annually data and Bai (2014) composed in a weekly frequent.
[20] Data is collected from http://www.londonstockexchange.com

by Unit Trusts calculated by Morningstar. The data is only available from November 2002 to June 2011.

3.9.1. Analysis of Monthly Data

Table 3.13 contains summary statistics of all the monthly variables. In the monthly variable series, AVDC, MFI, PCO, PCV and RSI show a relatively small degree of skew and almost no kurtosis. The Jarque-Bera test cannot reject the normal distribution at the 10% level for these variables. Compared to weekly variables, the lower frequency are usually better behaved. All other variables exhibit a skew and leptokurtic pattern. Except for AVDC, the sentiment indicators are highly auto-correlated, but all monthly returns have almost no serial correlation. ADF test results suggest that CCI, RSI, and VRA are non-stationary their first differences are stationary. Therefore, their first differences, $DCCI$, $DRSI$ and $DVRA$, will be used in future analysis.

3.9.2. Relation between sentiment proxies and equity returns

First, the monthly relation between the sentiment proxies and equity returns is analysed by regressing returns on the sentiment proxies. The sentiment proxies and their one period lagged are both included in the regressions. The autocorrelation coefficients indicate that returns of large-size stocks do not have autocorrelation. Returns of medium-size stocks and returns of small-size stock have first order autocorrelation, therefore one lag of return is included in the regression for medium and small-size stock returns. The regression results are reported in table 3.14. Compared to the weekly regression, there are fewer coefficients of returns of large stocks that are statistically significant in the monthly regression. This may imply that returns of large stocks are influenced less by investor sentiment in longer investment intervals. There are more sentiment coefficients significant for medium-size stocks than that of for large stocks, indicating that return of medium stock may be more likely to be affected by investor sentiment. Moreover, the significant variables indicate that returns of medium-size stocks are not only affected by institutional investor sentiment, but are also influenced by individual sentiment. Returns of small-size stock have the most amount of significant coefficients among three sizes of stocks, suggesting that returns of small stocks are the most likely to be affected by investor sentiment.

Table 3.13: Statistics of Monthly Basic Data

Table 3.13 provides summary statistics of the basic data series. The data are monthly and cover the period 1st January 1996 to 30th June 2011 (186 observations). Exceptionally the *CFLW* is available only from December 2002 (103 observations), and *BWSI* is available only to December 2010 (180 observations).

Variable definitions:
AVDC: Advances to declines ratio; **CCI** is UK Consumer Confidence Index; **DCCI**: first difference ofUK Consumer Confidence Index;**CEFD**: Closed-end Fund Discount; **CFLW** is mutual fund cash position; **MFI**: Money Flow Index; **NIPO** number of Initial Public Offer; **PCV**: Put-call volume ratio; **PCO**: Put-call open interest ratio; **RSI**: Relative Strength Index; **VOLA**: Realized volatility; **VRA**: Trading volume; **DVRA**: first difference ofTrading volume; **AAII**: American Association of Individual Investors index; **II**: American Investors Intelligence index; **GMIND**: German equity sentiment index; R_{big}: return on the large-size stock portfolio; R_{mid}: return on mid-size stock portfolio; R_{small}: return on small-size stock portfolio. **AC (1)** is the autocorrelation coefficient at one lag. **ADF** is Augmented Dickey-Fuller test statistic with maximum 5 lags.

Variable		Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Sum Sq. Dev.	AC (1)	ADF
Financial Market Indicators	*AVDC*	1.0128	0.2006	0.1868	2.7888	1.4278	7.4453	0.123	-11.9552***
	CCI	-6.3339	7.6095	-1.4060	5.0331	93.3157***	10712.2600	0.935	-2.1607
	DCCI	-0.06270	2.62874	-0.04516	3.9492	7.0077**	1271.49	-0.113	-8.3475
	CEFD	6.2322	1.9731	0.4069	4.0131	13.0875***	720.2009	0.866	-3.7325***
	CFLW	2.7018	0.6782	0.6087	3.4305	7.1562**	46.9154	0.659	-3.1226**
	MFI	39.9504	20.5517	0.4725	2.0322	14.1799***	78139.0800	0.954	-3.4668**
	NIPO	7.5591	6.1239	1.4958	6.3410	155.8657***	6937.8490	0.498	-3.8519***
	PCO	1.1818	0.1910	0.2211	2.0018	9.2373***	6.7495	0.88	-3.3829**
	PCV	1.2865	0.2653	0.2858	2.6710	3.3712	13.0238	0.45	-8.3381***
	RSI	68.7345	40.6715	-0.8405	1.9023	31.2387***	306021.5	0.936	-2.4104
	DRSI	-0.0057	14.2614	-1.4187	9.7217	410.33***	37423.36	-0.088	-14.7284***
	VOLA	1.0329	0.5649	2.4786	12.8092	936.1603***	59.0395	0.746	-5.1767***
	VRA	1.0119	0.0695	0.1083	4.2789	13.0389***	0.8941	0.825	-1.6848
	DVRA	-0.0001	0.0412	-0.3721	4.5026	21.671***	0.3124	0.048	-12.77717
Sentiment Index	*AAII*	0.1043	0.1984	0.1534	2.3353	4.1538	7.2809	0.429	-8.5466***
	BWSI	0.2122	0.6080	1.3434	5.2656	92.6413***	66.1647	0.973	-1.4221
	DBWSI	-0.0020	0.1378	-0.4524	5.8843	68.1550***	3.3817	0.134	-11.5897***
	GMIND	29.8855	36.8700	-0.4968	2.3965	10.4727***	251488	0.955	-3.4685***
	II	0.1829	0.1319	-0.7156	3.3733	16.9560***	32.18934	0.695	-5.7242***
Market Return	R_{big}	0.2566	4.2484	-0.7632	3.7521	22.4415***	3338.9970	0.053	-12.8289***
	R_{mid}	0.6114	5.2553	-1.0442	6.4129	124.0710***	5109.2810	0.174	-11.3504***
	R_{small}	0.1730	5.8419	-0.3890	7.3648	152.3416***	6313.5910	0.257	-10.4023***

Table 3.14: Monthly regressions of returns on sentiment proxies

Table 3.14 shows the results of estimating equations of the following form:

$$R_{size} = \alpha_0 + \sum_{i=0}^{2} \beta_{1,i} AVDC_{t-i} + \sum_{i=0}^{2} \beta_{2,i} DCCI_{t-i} + \sum_{i=0}^{2} \beta_{3,i} CEFD_{t-i} + \sum_{i=0}^{2} \beta_{4,i} MFI_{t-i} + \sum_{i=0}^{2} \beta_{5,i} PCV_{t-i} + \sum_{i=0}^{2} \beta_{6,i} PCO_{t-i} + \sum_{i=0}^{2} \beta_{7,i} RSI_{t-i} + \sum_{i=0}^{2} \beta_{8,i} VOLA_{t-i} + \sum_{i=0}^{2} \beta_{9,i} DVAR_{t-i} + \varepsilon_t$$

As there is some evidence of autocorrelation, the estimation method is OLS with Newey-West standard errors.The data are monthly and cover the period 1st January 1996 to 30th June 2011.

Variable definitions:
size = *big*, *mid* or *sml*; so, $\boldsymbol{R_{big}}$: return on the large-size stock portfolio; $\boldsymbol{R_{mid}}$: return on mid-size stock portfolio; $\boldsymbol{R_{small}}$: return on small-size stock portfolio; **AVDC**: Advances to declines ratio; D**CCI** is first deference of UK Consumer Confidence Index; **CEFD**: Closed-end Fund Discount; **MFI**: Money Flow Index; **PCV**: Put-call volume ratio; **PCO**: Put-call open interest ratio; **RSI**: Relative Strength Index; **VOLA**: Realized volatility; **DVRA**: first difference ofTrading volume.
Adj-R²: Adjusted R-squared; **S.E**: Standard Error of regression; **AIC**: Akaike information criterion.

	R_{big}		R_{mid}		R_{sml}	
Variable	**Coefficient**	**t-Statistic**	**Coefficient**	**t-Statistic**	**Coefficient**	**t-Statistic**
$AVDC_t$	13.0335***	7.7995	17.4371***	17.4638	15.7573***	9.8041
$AVDC_{t-1}$	-3.1893**	-2.3590	-1.2631	-0.7627	-0.5534	-0.2479
$DCCI_t$	0.1421**	2.2611	0.0744	1.0900	0.2203*	1.4453
$DCCI_{t-1}$	0.0727	0.8169	0.0852	1.2596	0.0453*	0.3787
$CEFD_t$	0.1740	0.8891	-0.2472	-1.2160	-0.6969*	-1.6612
$CEFD_{t-1}$	-0.0296	-0.1450	0.5081**	2.5561	0.9483***	2.6869
MFI_t	0.0051	0.3024	0.0365**	2.6045	0.0447**	2.2486
MFI_{t-1}	-0.0045	-0.2692	-0.0239*	-1.7721	-0.0236	-1.3236
PCV_t	-0.1970	-0.0809	0.1884	0.0812	-0.4415	-0.1311
PCV_{t-1}	0.8004	0.3128	-2.9299	-1.3229	-1.9296	-0.5835
PCO_t	-1.4910*	-1.6877	-0.6334	-0.6964	-0.3927	-0.3037
PCO_{t-1}	-0.1583	-0.1381	0.2231	0.2571	-0.5716	-0.4917
$DRSI_t$	0.0002	0.0097	-0.0225	-1.5935	-0.0092	-0.5325
$DRSI_{t-1}$	-0.0041	-0.2606	-0.0177	-1.4336	-0.0086	-0.4773
$VOLA_t$	-3.5314***	-6.2659	-4.6256***	-8.3867	-4.5246***	-4.3578
$VOLA_{t-1}$	1.8892***	3.3176	2.9442***	4.9464	3.2407***	3.0431
$DVRA_t$	-3.9438	-0.8244	-5.8532	-1.3722	-5.5994	-1.0016
$DVRA_{t-1}$	0.2255	0.0486	-2.2373	-0.5282	-9.9685*	-1.8444
Adj-R²	0.6396		0.8203		0.6995	
S.E	2.5627		2.2384		3.2166	
F-Statistic	19.0451		44.9674		23.4173	
AIC	4.8176		4.5518		5.2768	

3.9.3. Composition of monthly investor sentiment indices

As when constructing the weekly index, the first step to compose the monthly investor sentiment index is to estimate the first principal component of the sentiment proxies and their lags. This gives the first-stage index ($Index$) with 16 loadings.

$$\begin{aligned} Index_t = {} & 0.1061AVDC_t + 0.1652AVDC_{t-1} - 0.3528CEFD_t - 0.3400CEFD_{t-1} \\ & + 0.2857MFI_t + 0.2786MFI_{t-1} + 0.3154PCO_t + 0.2982PCO_{t-1} \\ & + 0.2194PCV_t + 0.2044PCV_{t-1} + 0.0201DRSI_t + 0.0273DRSI_{t-1} \\ & - 0.3666VOLA_t - 0.3845VOLA_{t-1} + 0.0164DVRA_t \\ & + 0.0065DVRA_{t-1} \end{aligned}$$

The second step is to compute the correlation between the $Index$, and the current and lagged values of each of the proxies. In each pair of the lead and lag variables, whichever has higher correlation with the $Index$ will be used in the final stage to produce an index, $SENT$, as follows:

$$\begin{aligned} SENT_t = {} & 0.2905AVDC_{t-1} - 0.4572CEFD_t + 0.3969MFI_t + 0.4047PCO_t \\ & + 0.2983PCV_t + 0.0759DRSI_{t-1} - 0.5386VOLA_{t-1} - 0.0184DVRA_t \end{aligned}$$

The correlation between the 16-term $Index$ and the $SENT$ index is 0.96, indicating that little information is lost in dropping the eight terms with other time subscripts. The first principal component explains 32% of the sample variance suggesting that the principle factor captures some of the common variation.

PCO, PCV, and $VOLA$ are again used for composing monthly institutional sentiment index ($SENT^p$). Applying the same method and procedure above, the institutional sentiment index is produced thus:

$$SENT_t^p = 0.6534PCO_t + 0.5820PCV_t - 0.4841VOLA_{t-1}$$

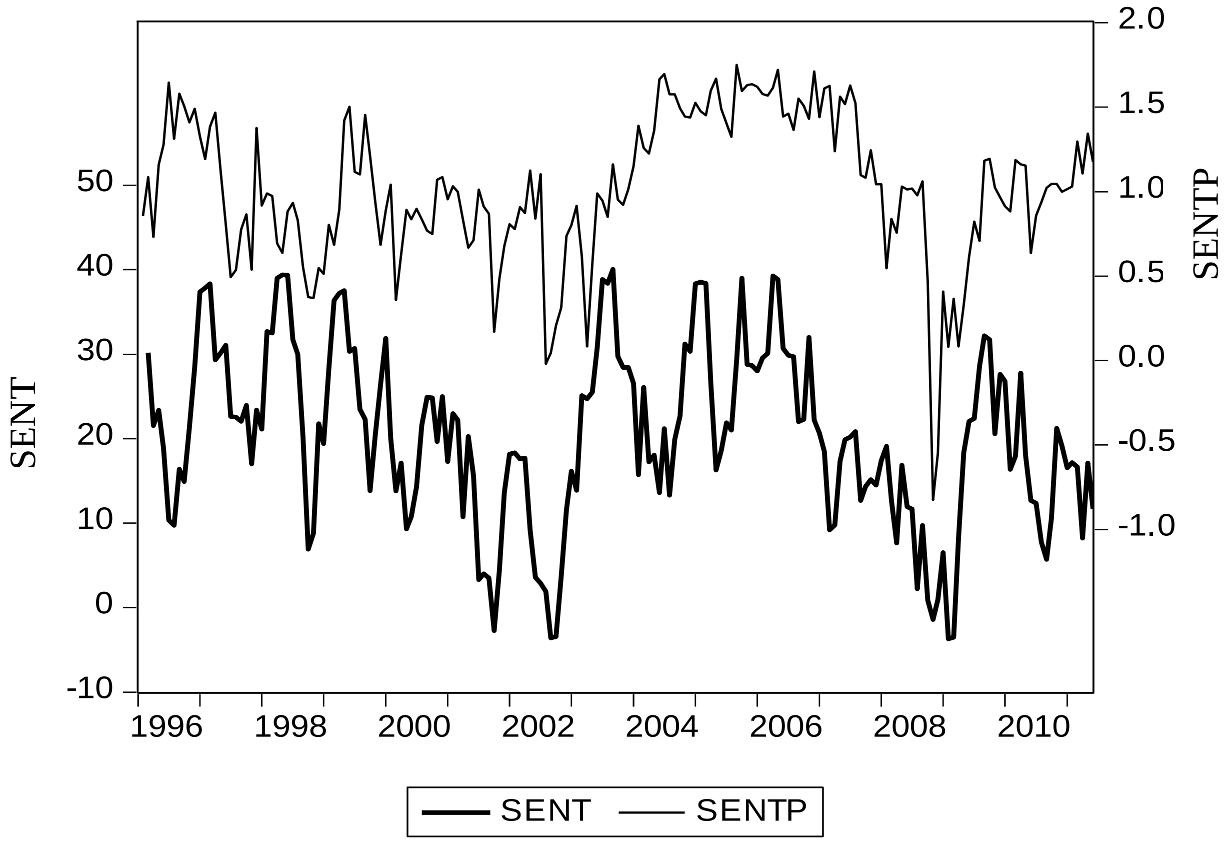
The same process as before as need to examine whether the use of PCO, PCV, and $VOLA$ in both constructing $SENT$ and $SENT^p$ will cause an overlapping problem(Section 3.3). A market sentiment index, $SENT^m$, is constructed by excluding PCO, PCV, and $VOLA$:

$$SENT_t^m = 0.5404AVDC_{t-1} - 0.5355CEFD_t + 0.6229MFI_t + 0.1789RSI_{t-1} - 0.0344DVRA_t$$

In this case, the first principal component explains 33% of the sample variance, implying that the common variation captured by the one factor has not changed much with PCO_t, PCV_t, and $VOLA_{t-1}$being excluded. This may suggest that $SENT_t^m$ captures the same factor as $SENT_t$. Moreover, the correlation coefficient of $SENT_t^m$ and $SENT_t$ is 0.9548, and it is statistically significant at the 1% level. Similar to the weekly result, $SENT_t^m$ is 99.97% correlated to $SENT_t$, suggesting that the UK market sentiment indexes which are constructed including or excluding the institutional sentiment proxies are very similar. This suggests there is hardly a problem of overlapping in the indexes$SENT_t$ and $SENT^p$ by includingPCO_t, PCV_t, and $VOLA_{t-1}$ in the construction of $SENT_t$.

Monthly $SENT$ and $SENT^p$ are plotted in Figure 3.2. Monthly $SENT$ and $SENT^p$ display quite similar patterns. Both sentiment indexes are generally hovering around their means. Individually, market sentiment, $SENT$, generally stays above its mean in 1996 and 1997, then has a sharp fall from early 1998, and reaches a relatively low point in late 1998. This fall can be seen as a reflection of the second phase of the Asian financial crisis. Market investor sentiment bounces back in the first half of the year 1999 and then starts to slide down until reaching one of the lowest points in early 2002. This may reflect the dotcom bubble crash. It stays at a low level during the year 2002, and then rises up to a very high level in late 2003 and then stays way above the mean until mid 2007 when the 2007-8 global financial crisis started. Market sentiment, $SENT$, falls down to one of its lowest point at late 2008 when Lehman Brothers declared bankruptcy, and stays there until early 2009. It then reverses back to a high level in about two months, and stays at that level until early 2010. $SENT$stays around the mean for the rest of sample period.

Figure 3.2: Monthly composed investor sentiment indexes



Institutional sentiment, $SENT^p$, looks more volatile than market sentiment. It is at a relatively high level in mid 1996 while $SENT$ was at around its mean level, and stays there until mid 1997 when the Asian financial crisis started. During late 1997 and early 1999, institutional sentiment stays low with a sharp spike upwards in early 1998 in the short period of market stability after the first phase of the Asian financial crisis. The $SENT^p$ spikes high in mid 1999 and stays at a relatively high level for most of the year in the period of the Dotcom bubble, then returns low in late 1999, shortly before the bubble crash, whereupon it stays under the average level until late 2003. From early 2004 to early 2008, $SENT^p$ has a long period of far higher than average, compared to $SENT$'s moderate higher than mean. In mid 2008 institutional sentiment has a sharp fall to its lowest point in the entire sample period, which is similar to $SENT$ reflecting the bankruptcy of Lehman Brothers, before reverting gradually back around its mean in early 2010.

The statistical summary (Table 3.15A Panel A) shows that, similar to weekly sentiment indices, UK monthly investor sentiment is highly autocorrelated, which is very similar to US and European investor sentiment. This suggests that investor sentiment is persistent.

Table 3.15A Panel B correlates the monthly sentiment measures. The majority of the correlations between the constructed sentiment indices and component variables are similar to those in the weekly frequency. $SENT$is highly correlated to MFI_t , $VOLA_{t-1}$ and $CEFD_t$, which suggests that the factor extracted represented both individual and institutional investors. There is no correlation between $SENT$and PCV. Different from weekly data, monthly $SENT$ does not correlate to the trading volume, $DVRA$. Similar to weekly data, $SENT^p$, it not only has high correlation to the component variables, but also has strong correlation with the non-component sentiment indicators. The coefficients for $CEFD_t$ and MFI_t show that institutional sentiment correlates highly to market sentiment indicators. This is confirmed by the 44% correlation of $SENT$and $SENT^p$, which is very similar to 40% of correlations between weekly $SENT$ and $SENT^p$.

Both the market sentiment index and the institutional sentiment index have the lowest correlation with trading volume. As with the weekly data, trading volume has not more than 20% correlation to other sentiment measures and in the monthly data, there is no significant correlation between them. Compared to other components, the one period lagged realised volatility, $VOLA_{t-1}$, has very high correlation to most of the sentiment measures, indicating that volatility has a strong link to investor sentiment.

The correlation tests also show that both $SENT$and $SENT^p$, have strong correlation to CFLW. Brown & Cliff (2004) expect the cash holdings to be more correlated with institutional sentiment than with individual sentiment. The correlation coefficient of CFLW and $SENT^p$ is -0.62 comparing to -0.43 of correlation between CFLW and $SENT$. This confirms Brown & Cliff (2004)'s expectation of stronger correlation between mutual fund cash position and institutional sentiment. It, in one way, suggests that the constructed UK sentiment indices are good measures of different groups of UK investor sentiment. The direct measure, Consumer Confident Index (CCI), is widely used as a measure of investor sentiment, particularly individual sentiment. The correlation coefficients of DCCI and SENT are greater than that of DCCI and $\mathrm{SENT^p}$, which may be a indication of SENT capturing some individual sentiment, though neither of the coefficients is significant. The p-value of the coefficient of DCCI and SENT is 0.1182 which indicates that the probability of DCCI correlating to SENT is fairly high and therefore, SENT may, in some degree, relate to some individual investor sentiment. Consumer's activities of savings and spending can be heavily influenced by the general macroeconomic and market fundamental factors, and it is not necessarily just reflected by their sentiment. This is confirmed by the correlations between DCCI and other investor sentiment proxies. DCCI is only statistically correlated to AVDC and does not correlate to all other indicators. This may suggest that DCCI does not capture investor sentiment as much as it is expected, and this would be one of the reasons for the weak correlation between DCCI and SENT.

Baker & Wurgler (2006) suggest that the number of Initial Public Offerings (NIPO) can be interpreted by the investor sentiment. The correlation between $SENT$ and NIPO is statistically significant, suggesting that $SENT$ may reflect investor sentiment. However, this correlation may reflect a common economic cycle component, as NIPO may also change with the economic cycle. The index that is extracted by principal components method may be not a common sentiment component but a common economic component since the principal components analysis cannot distinguish between them (Baker & Wurgler, 2006).

A regression of the composed index on macroeconomic indicators is conducted to examine whether it is reflected in common macroeconomic news. UK Index of Production provides an indicator of growth in the output of production industries and it is a key component of UK gross domestic production (GDP) measures. It is more likely that it is a distinctive macro variable which reflects the business cycle and cannot be confused with sentiment as might be argued for the interest rates. Interest rates such as a 3 month T-bill rate and a 10 year government bond rate are always used as macroeconomic indicators because changes of the rates are viewed as a reflection of business cycle and monetary policy. However, investors in the money markets may also make their decisions under the influence of sentiment, which leads to changes of interest rates also reflecting investor sentiment factors. The growth in the UK Index of

Production[21], *IOP*, is therefore used as the indicator of UK macroeconomics in the investigation.

Regressing *SENT* on *IOP* and its lagged term allows investigation of whether *SENT* reflects a common economic factor rather than investor sentiment. The regression shows evidence of residual serial correlation. In order to deal with autocorrelation in the dynamic model, a lagged term of *SENT* is added in the regression:

$$SENT_t = \alpha + \delta_0 SENT_{t-1} + \delta_1 IOP_t + \delta_2 IOP_{t-1}$$

where *IOP* is the growth in the UK index of productions, and the estimated results are summarised in Table 3.5C.

The coefficients for both IOP_t and IOP_{t-1} are not significant, indicating that the macroeconomic indicator has no explanatory power to the constructed index, $SENT$. Moreover, the adjusted R-squared of the model which includes the macroeconomics factors, decreases 0.0002 from that of the model excluding the macroeconomics factors. This suggests that the macroeconomics factors have very little effect on $SENT$ (only 0.02%). This confirms that the component that was extracted from the sentiment proxies is likely to be a common investor sentiment factor.

A regression of $SENT^p$ on *IOP* and its lagged term is conducted using model:

$$SENT_t^p = \alpha + \theta_0 SENT_{t-1}^p + \theta_1 IOP_t + \theta_2 IOP_{t-1}$$

where *IOP* is the growth in the UK index of productions, and the estimated results are also summarised in Table 3.5C.

The coefficient of IOP_t is significant but IOP_{t-1} is not, which suggests that the macroeconomic factor has some explanatory power to $SENT^p$. However, the coefficient of IOP_t is 0.04 indicating that every unit change of IOP only affects 0.04 unit of $SENT_t^p$, which can be seen as very small impact. The adjusted R-squared of the model that includes the macroeconomic factors, decreases 0.005 from that of the model

[21] The growth in the Index of Production is the first difference of Index of Production. The Index of Production data is collected from The office for National Statistics (ONS) http://www.ons.gov.uk/

excluding the macroeconomics factors. This suggests that the macroeconomic factors have a very small effect on $SENT_t^p$ (0.5%), which also confirms that the factor extracted from the component sentiment proxies is likely to be a common investor sentiment factor rather than a common economics component.

Additionally, a second index is constructed by removing the common economic factors from each of the sentiment proxies. Following Baker Wurgler (2006) procedure, regressing each of the eight sentiment proxies on *IOP*, the residuals from the regressions may be cleaner proxies for investor sentiment. An index of the orthogonalized proxies is composed by following the same procedure as before:

$$SENT_t^r = 0.1933AVCD_{t-1}^r - 0.4407CEFD_t^r + 0.3516MFI_{t-1}^r + 0.4526PCO_t^r \\ + 0.3890PCV_t^r + 0.0539RSI_{t-1}^r - 0.5315VOLA_{t-1}^r + 0.0573DVRA_{t-1}^r$$

where the superscript, r, represent the sentiment index and the proxies are the orthogonalized correspond variables.

$SENT_t^r$ retains most of the appealing properties of SENT in terms of the signs and the timing of the components. Only MFI_{t-1}^r appeals different timing, and $DVRA_{t-1}^r$ has diffident sign and timing. A summary of the correlations of the sentiment measures is reported in Table 3.5B. The orthogonalized sentiment measures are plotted against their original respectively in Figure 3.3. The plots[22] show that orthogonalizing to macro variables does not significantly affect any component of the index (Panel 1-7) and the overall index. The correlation tests also suggest that $SENT$ and $SENT^r$ are highly correlated (80%). This indicates that $SENT$ may capture the variables which reflect investor sentiment.

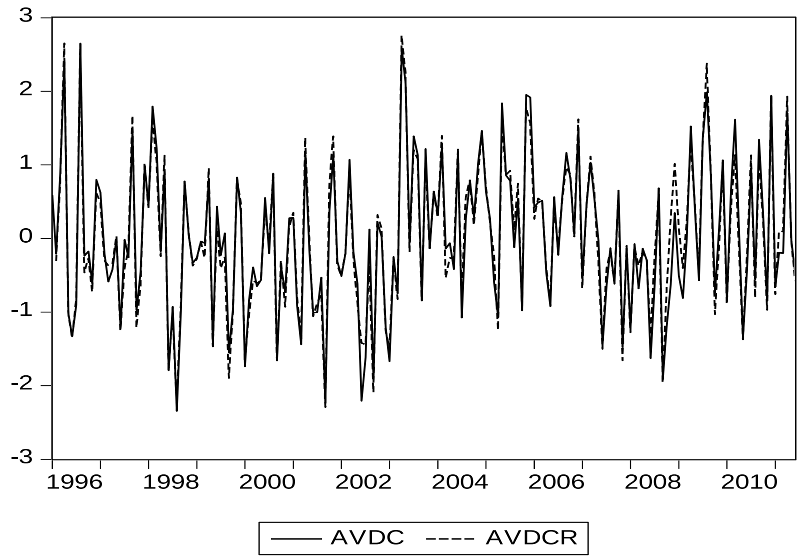
The same procedure has been conducted for the institutional sentiment and the orthogonalized institutional sentiment index is:

$$SENT_t^{p,r} = 0.6474PCO_t^r + 0.5932PCV_t^p - 0.4785VOLA_t^p$$

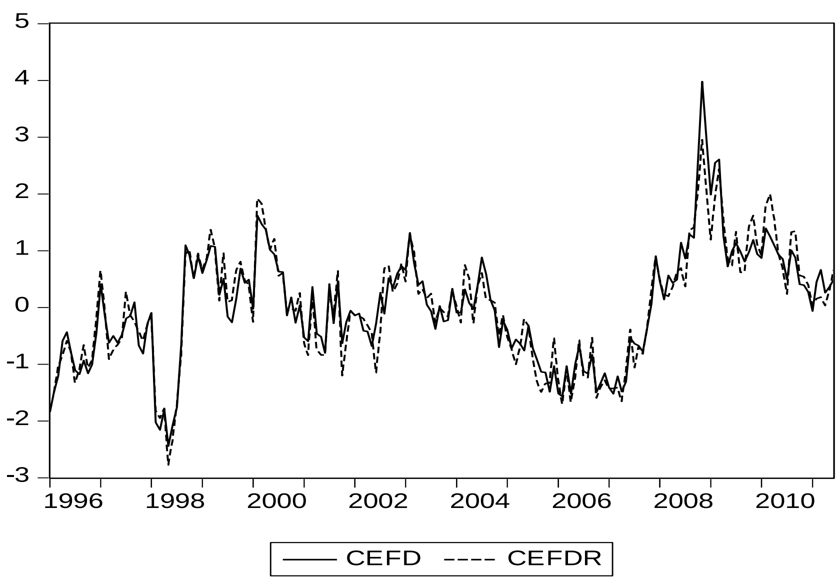
[22] The variables are standardized sentiment measures in the plots.

where the superscript, r, represent the sentiment index and the proxies are the orthogonalized corresponding variables. The statistic summary and correlations are also reported in Table 3.5B. $SENT_t^{p,r}$ retains all of the appealing properties of $SENT_t^{p}$ in terms of the signs and the timing of the components. The plot of $SENT_t^{p,r}$ against $SENT_t^{p}$ (Figure 3.3 Panel 11) suggests that orthogonalizing macro variables does not significantly affect the sentiment index. Moreover, the correlation test indicated that $SENT_t^{p,r}$ and $SENT_t^{p}$ are highly correlated (more than 97%), which suggest that both indices capture very similar factors, likely to be the institutional sentiment.

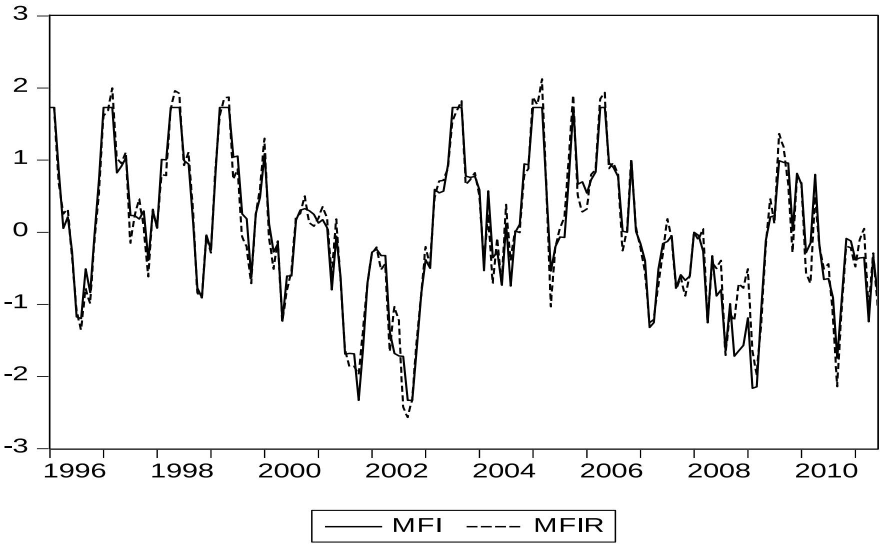
Panel 1 AVDC and AVDC^r



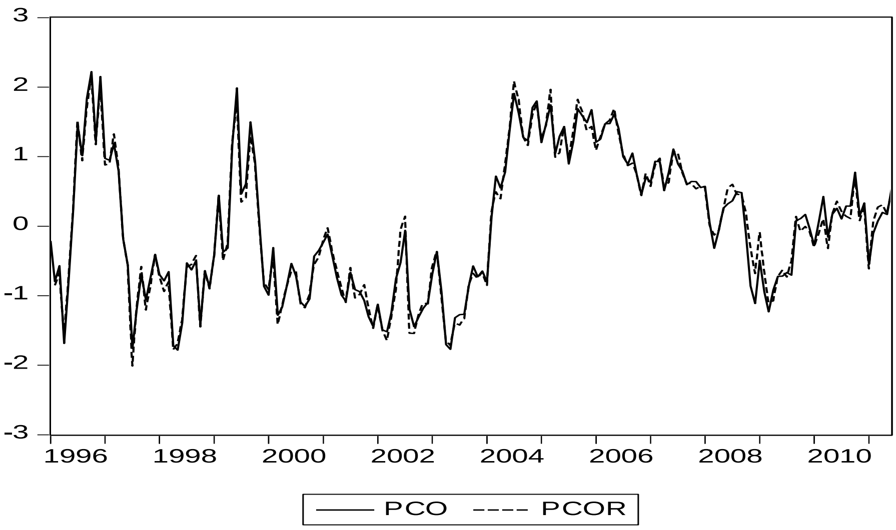
Panel 2 CEFD and CEFD^r



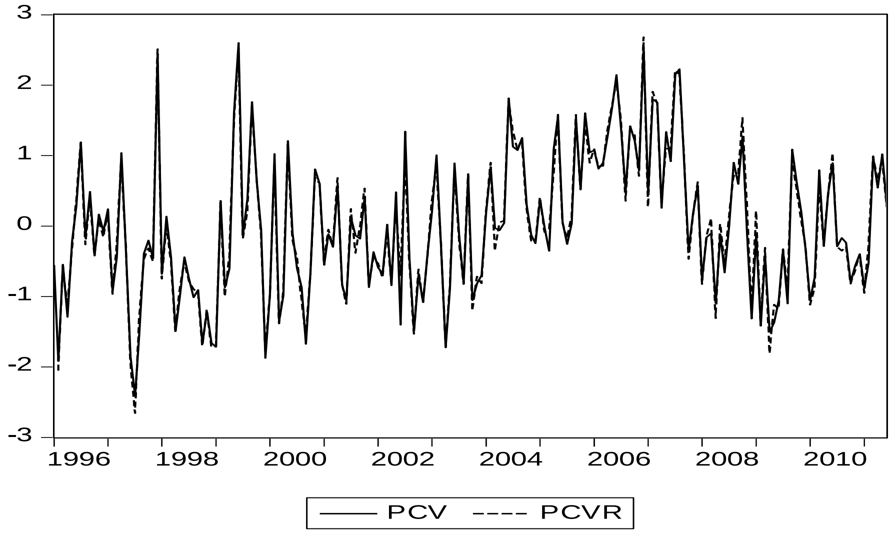
Panel 3 MFI and MFI^r



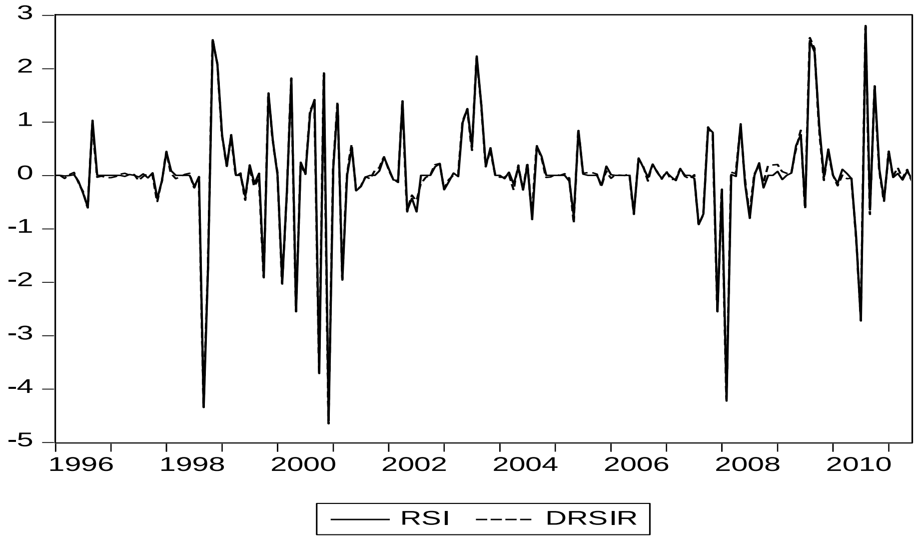
Panel 4 PCO and PCO^r



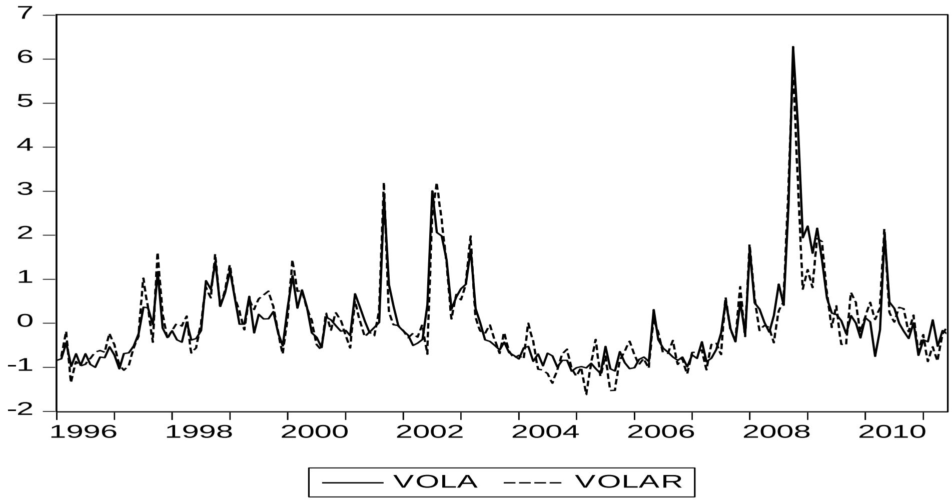
Panel 5 PCV and PCV^r



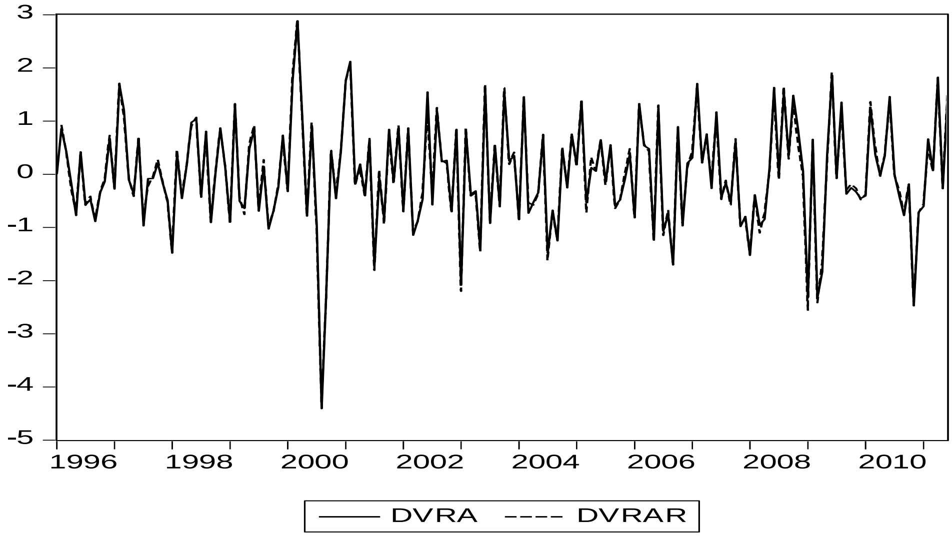
Panel 6 DRSI and DRSI^r



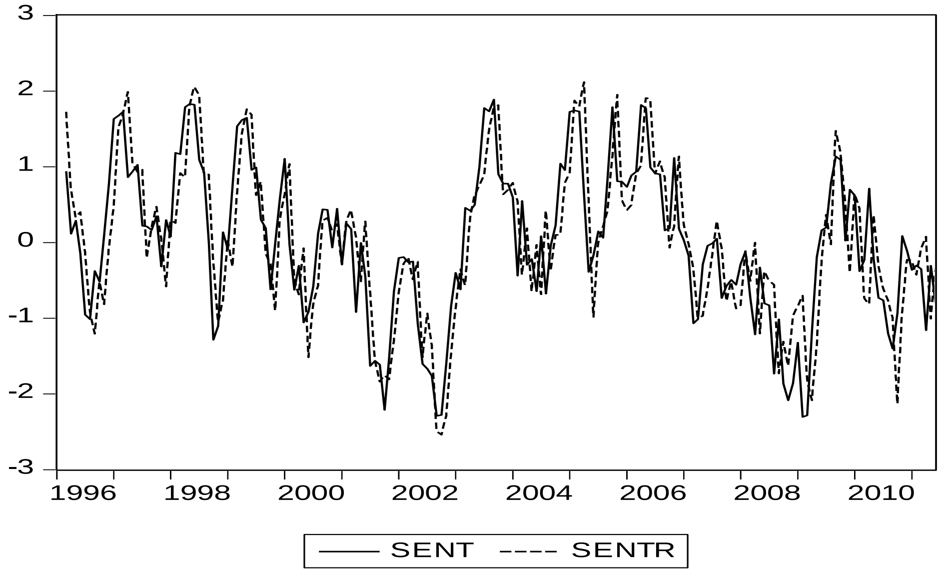
Panel 7 VOLA and VOLA^r



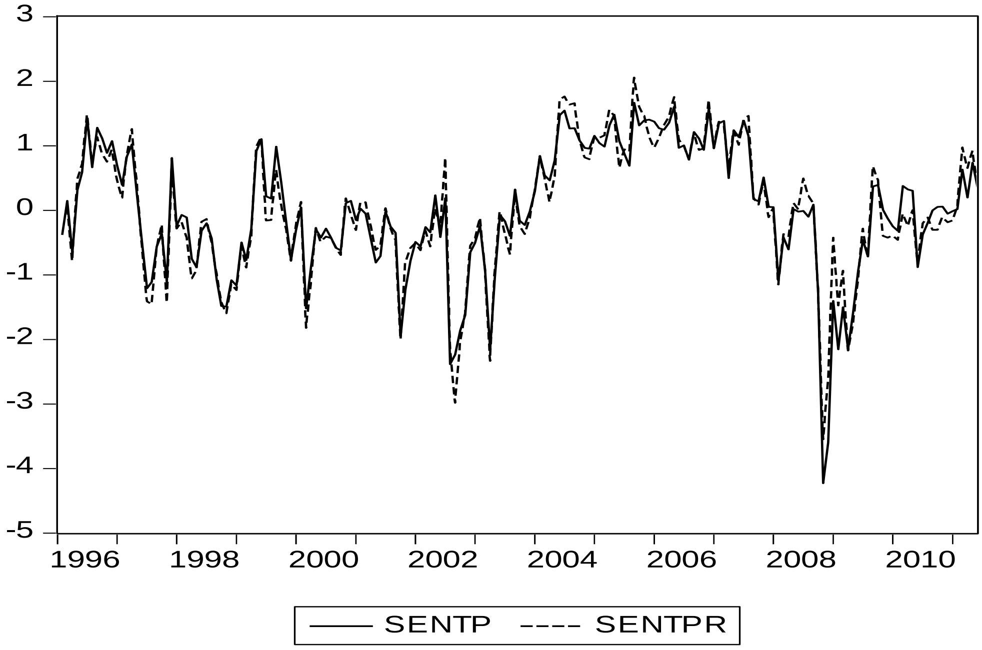
Panel 8 DVRA and DVRA^r



Panel 9 SENT and $SENT^r$



Panel 10 $SENT^p$ and $SENT^{p,r}$



Panel 11 $SENT^{r}$ and $SENT^{p,r}$

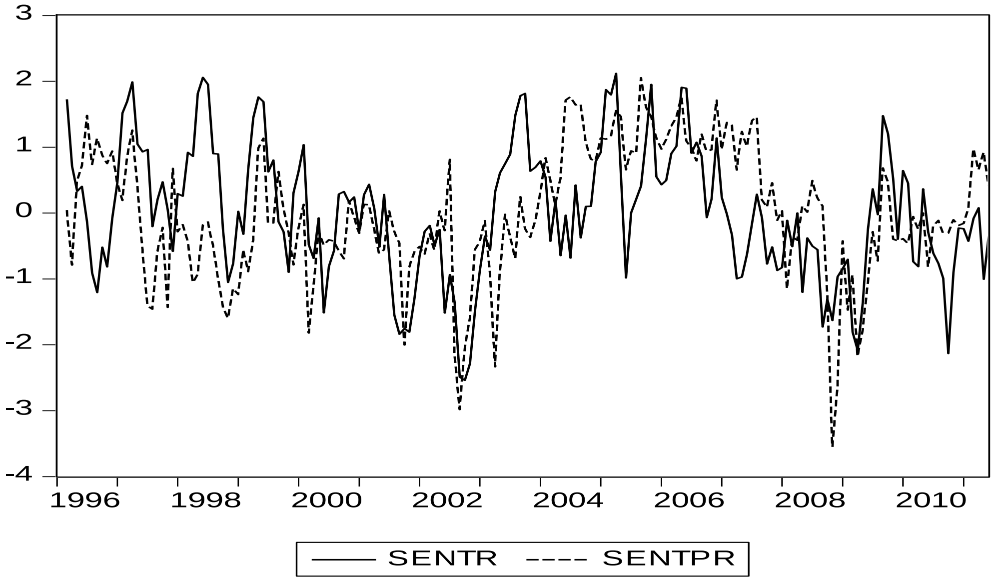


Figure 3.3: Investor sentiment index and the components

AVDC: Advances to declines ratio; **AVDC^{r}**: the orthogonalized Advances to declines ratio; **CEFD**: Closed-end Fund Discount; **CEFD^{r}**: the orthogonalized Closed-end Fund Discount; **MFI**: Money Flow Index; **MFI^{r}**: the orthogonalized Money Flow Index; **PCV**: Put-call volume ratio; **PCV^{r}**: the orthogonalized Put-call volume ratio; **PCO**: Put-call open interest ratio; **PCO^{r}**: the orthogonalized Put-call open interest ratio; **DRSI**: the first difference of Relative Strength Index; **DRSI^{r}**: the orthogonalized of the first difference of Relative Strength Index; **VOLA**: Realized volatility; **VOLA^{r}**: the orthogonalized Realized volatility; **DVRA**: first difference ofTrading volume; **DVRA^{r}**: the orthogonalized first difference of Trading volume; **SENT**: UK market sentiment; **SENT^{r}**: the orthogonalized UK market sentiment; **SENT^{P}**: UK institutional sentiment; **SENT^{p,r}**: the orthogonalized UK institutional sentiment. The data are monthly and cover the period 1st January 1996 to 30th June 2011. The variables are standardized when they are plotted.

Table 3.15A: Properties of monthly UK Investor Sentiment Indices

Panel A reports summary statistics of the constructed investor sentiment indexes: UK market sentiment (SENT) and UK institutional sentiment (SNETP)
Panel B shows pairwise correlation coefficients.
Panel C shows p-values for the F statistics from bilateral Granger causality tests

Variable definitions:
SENT: UK market sentiment; **SENT^{P}**: UK institutional sentiment; **AVDC**: Advances to declines ratio; **CEFD**: Closed-end Fund Discount; **MFI**: Money Flow Index; **PCV**: Put-call volume ratio; **PCO**: Put-call open interest ratio; **RSI**: Relative Strength Index; **VOLA**: Realized volatility; **DVRA**: first difference ofTrading volume.The data are monthly and cover the period 1st January 1996 to 30th June 2011.
ADF is the Augmented Dickey-Fuller test with a maximum of 12 lags.***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

Panel A: Statistical summary of Weekly sentiment indices

Variable	Mean	Std Dev.	Skewness	Kurtosis	Jarque-Bera	ADF	Autocorrelations at lags 1-5				
							1	2	3	4	5
SENT	20.3275	10.4377	-0.1456	2.5854	1.9680	-3.3222**	0.821***	0.665***	0.511***	0.350***	0.176**
SENT^{P}	1.0212	0.4356	-0.8064	4.4858	37.0646***	-4.4809***	0.801***	0.665***	0.579***	0.539***	0.493***

Panel B: Investor sentiment correlation coefficients

	$SENT_t$	$SENT^P_t$	$AVDC_t$	$CEFD_t$	MFI_t	PCO_t	PCV_t	RSI_t	$DVRA_t$	$VOLA_t$
$AVDC_{t-1}$	0.3728***	0.2304***	0.1232*	-0.2370***	0.3573***	0.0654	-0.0866	0.4950	0.0768	-0.3717***
$CEFD_t$	-0.4576***	-0.5454***	-0.1347*	1	-0.3866***	-0.2569***	-0.2015***	-0.2015***	-0.0407	0.6141***
MFI_{t-1}	0.9899***	0.3660***	0.1106	-0.3866***	1	0.1777**	0.0238	0.1285*	0.0369	-0.4512***
PCO_t	0.2203***	0.7949***	0.0568	-0.2569***	0.1777**	1	0.6231***	0.1285*	0.0307	-0.3905***
PCV_t	0.0780	0.6798***	0.0518	-0.2015***	0.0238	0.6231***	1	-0.1475**	0.0161	-0.1655**
$DRSI_{t-1}$	0.2309***	0.0618	-0.0224	0.0106	0.1346*	0.0159	-0.0056	-0.0876	-0.0900	-0.0743
$VOLA_{t-1}$	-0.5495***	-0.8423***	-0.0599	0.6354***	-0.4869***	-0.4548***	-0.2313***	-0.1023	0.0849	0.7476***
$DVRA_t$	-0.00177	-0.0389	0.0211	-0.0407	0.0369	0.0307	0.0161	-0.0023	1	0.0030
$CFLW_t$	-0.4258***	-0.6157***	-0.1001	0.6061***	-0.3609	-0.3837***	-0.3780***	-0.1267	-0.0878	0.5758***
$DCCI_t$	0.1158	0.0285	0.1440*	0.0240	0.1023	-0.0016	-0.0017	0.0843	-0.0676	-0.1208
$NIPO_t$	0.1588**	0.0829	0.0634	-0.2794***	0.1468**	-0.0503	-0.1148	-0.1174	0.0627	-0.2376***
$SENT_t$	1	0.4360***	-	-	-	-	-	-	-	-

Panel C: Granger causality tests of SENT

	SENT^{P}	
	SENT does not Granger Cause ***SENT^{P}***	***SENT^{P}*** does not Granger Cause ***SENT***
SENT	0.0732	0.3970

Table 3.16B: Properties of monthly UK Investor Sentiment Indices

Panel A reports summary statistics of the constructed investor sentiment indexes: UK market sentiment ($SENT^r$) and the orthogonalized UK market sentiment ($SNET^r$)
Panel B shows pairwise correlation coefficients.

Variable definitions:
SENT: UK market sentiment; **SENT^{p}**: UK institutional sentiment; **SENT^{r}**: the orthogonalized UK market sentiment; **SENT^{p,r}**: the orthogonalized UK institutional sentiment; **AVDC^{r}**: the orthogonalized Advances to declines ratio; **CEFD^{r}**: the orthogonalized Closed-end Fund Discount; **MFI^{r}**: the orthogonalized Money Flow Index; **PCV^{r}**: the orthogonalized Put-call volume ratio; **PCO^{r}**: the orthogonalized Put-call open interest ratio; **RSI^{r}**: the orthogonalized Relative Strength Index; **VOLA^{r}**: the orthogonalized Realized volatility; **DVRA^{r}**: the orthogonalized first difference of Trading volume.The data are monthly and cover the period 1st January 1996 to 30th June 2011.**ADF** is the Augmented Dickey-Fuller test with a maximum of 12 lags.***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

Panel A: Statistical summary of Weekly sentiment indices

Variable	Mean	Std Dev.	Skewness	Kurtosis	Jarque-Bera	ADF	Autocorrelations at lags 1-5				
							1	2	3	4	5
$SENT^r$	0.0417	8.9446	-0.0054	2.7438	0.5040	-4.9724***	0.767***	0.582***	0.408***	0.270***	0.093
$SENT^{p,r}$	0.0022	0.4166	-0.4722	3.4283	8.2444	-5.0334***	0.753***	0.587***	0.507***	0.484***	0.473***

Panel B: Investor sentiment correlation coefficients

	$SENT_t^r$	$SENT_t^{p,r}$	$AVDC_t^r$	$CEFD_t^r$	MFI_t^r	PCO_t^r	PCV_t^r	$DRSI_t^r$	$DVRA_t^r$	$VOLA_t^r$
$AVDC_{t-1}^r$	0.0963	0.1887**	0.0995	-0.1712**	0.3048***	0.0363	-0.0817	0.4952***	-0.0876	-0.3111***
$CEFD_t^r$	-0.3937***	-0.4810***	-0.0868	1	-0.3350***	-0.2407***	-0.2122***	-0.0127	-0.0499	0.5720***
MFI_{t-1}^r	0.9905***	0.3422***	0.0764	-0.3010***	0.7721***	0.1520**	0.1294*	-0.0659	0.1341*	-0.3378***
PCO_t^r	0.1923***	0.7834***	0.0295	-0.2407***	0.1629**	1	0.6217***	-0.0715	0.0435	-0.3761***
PCV_t^r	0.1658**	0.7083***	0.0297	-0.2122***	0.0279	0.6217***	1	-0.1520**	0.03869	-0.1608**
$DRSI_{t-1}^r$	0.1983***	0.0480	-0.0334	0.0356	0.1166	0.0279	-0.0016	-0.0906	-0.0900	-0.0496
$VOLA_{t-1}^r$	-0.4801***	-0.8280***	-0.0025	0.5424***	-0.3879***	-0.4211***	-0.2508***	-0.0836	0.0987	0.6546***
$DVRA_{t-1}^r$	0.0559	0.0536	0.0958	-0.0160	0.1211	0.0291	0.0952	0.0476	0.0432	0.0551
$SENT_t$	0.8037***									
$SENT_t^p$		0.9712***								

Table 3.17C: Reports the results of regression composed monthly UK Investor Sentiment Indices on macroeconomics indicator

Table 3.15C reports the results of estimating equations of the general form:

Including Economics Factors Model: $SENT_t^K = \alpha_0 + \delta_0 SENT_{t-1}^K + \delta_1 IOP_t + \delta_2 IOP_{t-1} + \varepsilon_t$

Excluding Economics Factors Model: $SENT_t^K = \alpha_0 + \delta_0 SENT_{t-1}^K + \varepsilon_t$

The estimation method is OLS, however when LM or/and ARCH is significant, the model is estimated by OLS with Newey-West standard errors. The data are monthly and cover the period 1st January 1996 to 30th June 2011. Exceptionally the *BWSI* is available only to December 2010.

Variable definitions:
$SENT^K$ = UK market sentiment (K=M), or institutional sentiment (K=P); **IOP**: the growth in UK Index of production.
***Significant at 1% level; **Significant at 5% level; *Significant at 10% level.

	SENT				***SENT^P***			
	Including Economics Factors		**Excluding Economics Factors**		**Including Economics Factors**		**Excluding Economics Factors**	
	Coefficient	**t-Statistic**	**Coefficient**	**t-Statistic**	**Coefficient**	**t-Statistic**	**Coefficient**	**t-Statistic**
α	3.8109***	3.8502	3.4758***	3.7187	0.2189***	4.2863	0.2044***	4.1566
$SENT_{t-1}$	0.8101***	18.7543	0.8245***	20.9271	0.7888**	17.1414	0.8013***	18.0735
IOP_t	0.4461	0.9092			0.0444**	2.0531		
IOP_{t-}	0.6494	1.3238			-0.0033	-0.1498		
Adj. R^2	0.6789		0.6787		0.6456		0.6402	
S.E.	5.9165		5.9181		0.2599		0.2619	
AIC	6.4150		6.4048		0.1645		0.1689	
LM test	1.8044		2.8254**		1.5072		1.0605	
ARCH	1.6949		1.6370		0.8369		0.8156	

3.9.4. Composed UK sentiment indexes and foreign sentiment measures

In order to investigate the relation between UK investor sentiment and foreign investor sentiment, two US survey sentiment indexes and one constructed investor sentiment index are used for analysis of the relationship between UK and US investor sentiment, and one German survey sentiment index is used in the analysis of relation between UK and European investor sentiment. AAII, II, and Baker & Wurgler sentiment index (BWSI) [23] represent US individual, institutional, and market investor sentiment respectively. German Market Indicator (GMI) [24], are used to represent European investor sentiment.

GMI is an indicator of German Economic Sentiment. It is published monthly by the Centre for European Economic Research (ZEW). The indicator is calculated from the results of the ZEW Financial Market Survey, with up to 350 financial analysts and institutional investors taking part in it. The sentiment index is constructed from the difference between the percentage share of survey participants that are bullish and the share of participants that are bearish for the expected German economy in the next six months. Since the index is conducted from the survey results based on institutional investors, it is seen as an index for German institutional sentiment. According to the UK Office for National Statistics, by the end of 2012, more than 53% UK quoted shares are owned by foreign investors, and among them 26% are owned by investors in Europe. As Germany is the largest single economy in Europe Union, investor sentiment in Germany could be a good representative of European investor sentiment. Unlike the weekly Sentix, data for GMI is available for the whole sample period, 01/01/1996 – 30/06/2010.

When looking at the relationship of investor sentiment between UK and foreign institutional sentiment (Table 3.16 Panel A), both $SENT^p$ and $SENT$ have very strong correlation with the US institutional survey sentiment index, II. They are also correlated with German institutional sentiment, although by rather less than with US institutional sentiment. Moreover, the correlation of $SENT^P$ and US individual sentiment is

[23] Data is availed on Jeffrey Wurgler website: http://people.stern.nyu.edu/jwurgler/
[24] GMI data is download from http://www.zew.de

insignificant while $SENT^P$ is strongly correlated with II. $SENT$ is also more highly correlated with II than with AAII.

The coefficient between $SENT$ and BWSI is significant, demonstrating that investor sentiment of these two countries are correlated on a market wide scale. It is worth noting that the correlation between BWSI and AAII is not significant, but the correlation between BWSI and II is suggesting that the constructed US sentiment index is more likely to capture US institutional sentiment. However, the correlation of BWSI and II is negative, which is different from the correlation between the Brown and Cliff (2004) constructed US sentiment and the survey institutional sentiment (II).

Both UK institutional sentiment and UK market sentiment have greater correlation with US institutional sentiment than that with European institutional sentiment. They have much weaker correlation to US individual and market sentiment. This implies that foreign institutional sentiment is more likely to have a greater impact on, or to be affected by, UK investor sentiment.

Granger-causality tests provide more evidence of the effect that foreign investor sentiment has on UK investor sentiment. The test results (Table 3.16 Panel B) show that it is more likely that both US individual and institutional sentiment Granger-cause UK investor sentiment but not vice versa. This means US individual or/and institutional sentiment leads to UK market or/and institutional sentiment, but UK investor sentiment does not lead to US individual or institutional sentiment. The Granger-causality relationships between US market sentiment (BWSI) and UK market and/or institutional sentiment, display a different picture. For UK market sentiment, there is not a statistically Granger-causal relationship to US market sentiment, i.e. neither UK market sentiment leads US market sentiment or vice versa. For UK institutional sentiment, it shows that the causal effect could be in both directions, i.e. US market sentiment is affected by UK institutional sentiment and vice versa. The causality tests also demonstrate that UK institutional sentiment is caused by European institutional sentiment but does not lead European institutional sentiment.

Table 3.18: Correlation and Granger causality tests: monthly UK and foreign investor sentiment

Panel A shows pairwise correlation coefficients among different sentiment indices.
Panel B shows p-values for the F statistics from bilateral Granger causality tests as between either of the UK indices (*SENT* or $SENT^{P}$) and any one of the US or German indices (*AAII*, *II*, or *GMI*)
Test 1: H_0: Granger-noncausality from the US/German index to the UK index.
Test 2: H_0: Granger-noncausality from the UK index to the US/German index.

Variable definitions:
SENT is UK market sentiment; $\mathbf{SENT^{P}}$ is UK institutional sentiment;**AAII** is American Association of Individual Investors index; **BWSI**: Baker & Wurgler sentiment index;**DCCI** is first deference of UK Consumer Confidence Index; **II** is American Investors Intelligence index; **GMI** is German equity sentiment index.The data are monthly and cover the period 1st January 1996 to 30th June 2011.
***Significant at 1% level; **Significant at 5% level; *Significant at 10% level.

Panel A: Correlation tests

	$SENT^{P}$	*SENT*	*DCCI*	*AAII*	*II*	*BWSI*	*GMI*
$SENT^{P}$	1.0000						
SENT	0.4360***	1.0000					
DCCI	0.0147	0.1175	1.0000				
AAII	-0.0412	0.2234**	0.1047	1.0000			
II	0.3554***	0.4500***	0.1233	0.4092***	1.0000		
BWSI	-0.0137	-0.1993***	-0.0982	0.0733	-0.1444*	1.0000	
GMI	0.2137***	0.3982***	0.1598**	0.2432***	0.2241***	-0.1136	1.0000

Panel B: Granger causality tests

	AAII		II		BWSI		GMI	
	Test 1	Test 2	Test 1	Test 2	Test 1	Test 2	Test 1	Test 2
SENT	0.0196	0.1881	<0.0001	0.9491	0.1772	0.1008	0.2671	0.4072
$SENT^{P}$	0.0494	0.2821	<0.0001	0.8885	0.0654	0.0168	0.0646	0.6025

Further regressions are run to robustly examine the relationship between UK investor sentiment and foreign investor sentiment. The UK sentiment index is regressed on their lagged terms and on the US sentiment indexes and the European sentiment index. US market sentiment, BWSI, has a slightly short sample period, which is from January 1996 to December 2010. The model therefore, is also estimated by excluding BWSI, with data covering the full sample period to compare whether the effect from foreign investor sentiment behaves differently. The model is:

$$S_t = \alpha_0 + \sum_{j=1}^{3} \alpha_j S_{t-j} + \sum_{i=0}^{3} \gamma_i AAII_{t-i} + \sum_{i=0}^{3} \delta_i II_{t-i} + \sum_{i=0}^{3} \theta_i\, GMI_{t-i} + \sum_{i=0}^{3} \vartheta_i BWSI_{t-i} + \omega_t \quad (3.15)$$

whereS_t is the composed UK sentiment indices $SENT$ and $SENT^{p}$ at time t.

Breusch-Godfrey serial correlation LM tests (up to 12 lags) indicates residual serial correlation in the OLS estimations, and in order to mitigate the problem, Newey-West HAC Standard Errors & Covariance (lag truncation=4) is applied in the estimation method. Following the same procedure as in the weekly analysis, the models are simplified by deleting insignificant variables.

For UK market sentiment (Table 3.17), the estimated coefficients of reconstructed models tell a very similar story to the original models. All the coefficients of BWSI are not significant demonstrating that US market sentiment does not have explanatory power for UK market sentiment. Estimated coefficients suggest that only US institutional sentiment has an impact on UK market sentiment. Similarly to the weekly data, a reverse effect also exists in the monthly regression, though most of the coefficients of foreign sentiment variables are not significant.

The estimations show that the UK market sentiment, $SENT$, is affected by both one lagged and two lagged of US institutional sentiment, since II_1 and II_3 are statistically significant at the 5% level. The coefficients for US market sentiment variables in model 1 and US individual sentiment and European Institutional sentiment in model 2 are insignificant. This suggests that UK market sentiment is not affected by US individual sentiment, European institutional sentiment or US market sentiment. It generally agrees with the results of Granger causality tests.

For the UK institutional sentiment (Table 3.17), Breusch-Godfrey serial correlation LM tests (up to 12 lags) indicate that there is no residual serial correlation in the four regressions, and ARCH test (2 lags) shows no heteroskedasticity as well. This suggests that the estimated parameters from OLS method are unbiased and efficient. The models are estimated first and the estimated results show that coefficients of higher order lagged terms are insignificant. The models are simplified by deleting insignificant variables. The improvement of the standard error suggests that the amended model can better fit the data.

Looking at estimated coefficients in model without *BWSI* first, the significant of $AAII_0$ and II_1 demonstrates that current US individual sentiment and one lagged US institutional sentiment have explanatory power to UK institutional sentiment. The coefficients for European Institutional sentiment variables are insignificant, indicating that European Institutional sentiment may have no effect on UK institutional sentiment. This confirms the Granger causality tests results, which show that US institutional sentiment has the highest significance level to Granger cause UK institutional sentiment, and European Institutional sentiment has the lowest significance level to Granger cause UK institutional sentiment. This strongly significant II_1, however, suggests a different effect of US individual and institutional sentiment on UK institutional sentiment.

The estimated II_1 and $BWSI_0$ are statistically significant in model 1, implying that one period lagged US institutional sentiment and current US market sentiment have an impact on UK institutional sentiment, however, the coefficients for US individual sentiment are still insignificant. This suggests that the explanatory power of US individual sentiment to UK institutional sentiment is overtaken by the US market sentiment.

Compared to weekly data, fewer foreign investor sentiment indices affect UK investor sentiment in monthly frequency. For example, US individual sentiment has a strong effect on both UK market and institutional sentiment in weekly frequency but has a weak marginal effect in monthly frequency. The reverse effect is also stronger in weekly frequency. This may because that investor sentiment in one country can directly affect sentiment in another country via investor herding instinct. Christie and Huang (1995) suggest that herding is generally a short-term behaviour. Internet message boards and globalized investment business make it possible that foreign sentiment becomes local. When fundamental information is incorporated slowly into decision making, investors tend to gradually adjust their investment decision and correct the behaviour. In both weekly and monthly frequency, US institutional sentiment has a significant and persistent impact on UK investor sentiment. This, in one way, confirms the hypothesis that domestic investors are likely to pay attention to foreign institutional sentiment to general foreign market sentiment. The fact that 53% of listed UK shares are owned by foreign investors and more than 82% of the foreign owners are institutional investors may be one of the reasons to explain the impact of foreign institutional sentiment on UK investor sentiment.

Table 3.19: Regression analysis of monthly $SENT$ on foreign sentiment indexes

Table 3.17 reports the results of estimating equations of the general form:

Model 1: $SENT_t^K = \alpha_0 + \sum_{i=0}^{3}\gamma_i AAII_{t-i} + \sum_{i=0}^{3}\delta_i II_{t-i} + \sum_{i=0}^{3}\theta_i\, GMI_{t-i} + \sum_{i=0}^{3}\vartheta_i BWSI_{t-i} + \sum_{i=1}^{3}\alpha_i SENT_{t-i}^K + \varepsilon_t$

Model 2: $SENT_t^K = \alpha_0 + \sum_{i=0}^{3}\gamma_i AAII_{t-i} + \sum_{i=0}^{3}\delta_i II_{t-i} + \sum_{i=0}^{3}\theta_i\, GMI_{t-i} + \sum_{i=1}^{3}\alpha_i SENT_{t-i}^K + \varepsilon_t$

The estimation method is OLS with Newey-West standard errors. The data are monthly and cover the period 1st January 1996 to 30th June 2011. Exceptionally the *BWSI* is available only to December 2010.

Variable definitions:

$SENT^K$ = UK market sentiment (K=M), or institutional sentiment (K=P); **AAII**: American Association of Individual Investors index; **II**: American Investors Intelligence index; **GMI**: German equity sentiment index. **BWSI**: Baker & Wurgler sentiment index, i.e. US market sentiment. t statistics are shown in parentheses. ***Significant at 1% level; **Significant at 5% level; *Significant at 10% level.

	SENT				***SENT^P***			
	Including BWSI 01/01/1996 - 31/12/2010		**Excluding BWSI 01/01/1996 - 30/06/2011**		**Including BWSI 01/01/1996 - 31/12/2010**		**Excluding BWSI 01/01/1996 - 30/06/2011**	
	Model 1	***Reconstructed model 1***	***Model 2***	***Reconstructed model 2***	***Model 1***	***Reconstructed model 1***	***Model 2***	***Reconstructed model 2***
$AAII_t$	0.0110 (0.3217)	0.0100 (0.3051)	0.0063 (0.2030)	0.0065 (0.2219)	-0.0016 (-1.2842)	-0.0015 (-1.3268)	-0.0022** (-1.8413)	-0.0018* (-1.7230)
$AAII_{t-1}$	0.0039 (0.1355)	0.0044 (0.1506)	0.0003 (0.0098)	-0.0006 (-0.0222)	-0.0002 (-0.1403)		-0.0005 (-0.3478)	
$AAII_{t-2}$	-0.0034 (-0.1268)	0.0105 (0.5143)	0.0017 (0.0675)	0.0079 (0.3812)	0.0009 (0.6404)		0.0014 (1.0676)	
$AAII_{t-3}$	0.0168 (0.7130)		0.0047 (0.2037)		0.0004 (0.3663)		0.0005 (0.3987)	
II_t	0.0714 (1.5367)	0.0747 (1.5546)	0.0722 (1.5680)	0.0781* (1.6611)	0.0029 (1.2080)	0.0032 (1.3964)	0.0029 (1.2850)	0.0032 (1.4684)
II_{t-1}	0.1463** (2.5796)	0.1592*** (2.8479)	0.1638*** (2.8698)	0.1659*** (3.0269)	0.0044 (1.5010)	0.0046** (2.1371)	0.0058** (2.1185)	0.0050*** (2.4212)
II_{t-2}	-0.1242** (-2.0731)	-0.1363*** (-3.1784)	-0.1511** (-2.7232)	-0.1543*** (-3.7428)	-0.0025 (-0.8582)		-0.0035 (-1.2424)	
II_{t-3}	-0.0030 (-0.0495)		-0.0011 (-0.0200)		0.0008 (0.3494)		0.0014 (0.5803)	
GMI_t	0.0688 (1.2732)	0.0672 (1.3695)	0.0735 (1.5109)	0.0738 (1.6171)	0.0011 (0.4416)	0.0003 (0.5911)	0.0005 (0.1923)	0.0005 (0.9259)
GMI_{t-1}	-0.0437 (-0.4371)	-0.0649 (-0.7822)	-0.0449 (-0.4932)	-0.0646 (-0.8393)	0.0033 (0.7845)		0.0031 (0.749)	
GMI_{t-2}	-0.0592 (-0.5127)	0.0079 (0.1594)	-0.0481 (-0.4406)	0.0047 (0.1092)	-0.0068 (-1.6111)		-0.0051 (-1.26618)	
GMI_{t-3}	0.0488 (0.7745)		0.0377 (0.6213)		0.0026 (1.0828)		0.0020 (0.8850)	
$BWSI_t$	-0.1772 (-0.0606)	-0.0891 (-0.0318)			0.2525 (1.6476)	0.2337* (1.6608)		
$BWSI_{t-1}$	-1.0259 (-0.2350)	-1.7286 (-0.4266)			0.0072 (0.0316)	-0.0657 (-0.3143)		
$BWSI_{t-2}$	-2.6046 (-0.5862)	0.8435 (0.2659)			-0.4033* (-1.7908)	-0.1799 (-1.2442)		
$BWSI_{t-3}$	2.8614 (0.8489)				0.1213 (0.7829)			
$SENT_{t-1}$	0.7688*** (11.1152)	0.7607*** (16.7962)	0.7826*** (11.4637)	0.7756*** (18.2760)				
$SENT_{t-2}$	0.0585 (0.5796)		0.0620 (0.6311)					
$SENT_{t-3}$	-0.0771 (-1.0209)		-0.0841 (-1.1819)					
$SENT^P_{t-1}$					0.6119*** (7.6233)	0.6937*** (14.7399)	0.6448*** (8.3546)	0.7126*** (15.7607)
$SENT^P_{t-2}$					0.0495 (0.5225)		0.0363 (0.3979)	
$SENT^P_{t-3}$					0.1149 (1.5005)		0.0942 (1.2754)	
Adj. R^2	0.7266	0.7315	0.7248	0.7292	0.6880	0.6855	0.6807	0.6809
S.E.	5.5441	5.4636	5.5065	5.4328	0.2483	0.2482	0.2477	0.2466
AIC	6.3705	6.3099	6.3340	6.2810	0.1582	0.0999	0.1309	0.0701
LM test	1.6125*	1.7714*	1.9497**	1.8485**	0.8258	0.6289	0.8647	0.8647
ARCH	0.5522	0.9297	0.8839	1.1858	0.2814	0.9891	0.6686	0.6686

3.10 Monthly Investor sentiment and equity returns

The returns are tested against all the market sentiment indices. Correlation tests in Table 3.18 Panel A show that returns of all size stocks in UK have the strongest correlation to US individual and institutional sentiment. This, in one sense, is suggested by the ownership of UK shares, 53% UK quoted shares are owned by foreign investors, and among them 48% are owned by investors in North America. [25] The correlation analysis also shows that returns of all size stocks hardly have any correlation to UK institutional sentiment. Return of medium and small size stocks have some correlation to UK market sentiment, but they are not as strong as to US investor sentiment. Returns of large and small-size stocks have some correlation with European Institutional sentiment. Returns of small stocks are those most widely correlated investor sentiments around the world amongst the three categories of stocks.

Granger causality test (up to 3 lags) are conducted to examine the causal relation between returns and investor sentiment indices (Table 3.18 Panel B). The results show that the US, UK and European investor sentiments do not Granger-cause returns of large stocks at the 10% significance level except US institutional sentiment. The test of Granger-noncausality II is rejected at the 5% significance level, suggesting that US institutional sentiment may Granger-cause returns of large stocks. The tests of Granger-noncausality also show that large stock returns are likely to lead the investor sentiments in these three countries except the US individual sentiment, AAII, and US market sentiment, BWSI. This is similar to the results of Wang, Keswani & Taylor (2006).

For medium stocks, the results suggest that UK, US and European investor sentiment does not cause stock price changes but medium stock returns do appear to have some causal effect on UK and European investor sentiments and US institutional sentiment. The results also indicate that there is no causal relationship between medium stocks and US individual and market sentiment in either direction.

[25] Ownership of UK Quoted Shares 2012, *Office for national statistic*

Table 3.20: Correlation and Granger causality test for monthly stock returns and investor sentiment

Panel A shows pairwise correlation coefficients between sentiment indices and different size UK stock portfolios.
Panel B gives p-values for the F statistics from bilateral Granger causality tests as between the sentiment indices and the returns on different size UK stock portfolios.
Test 1: H_0: Granger-noncausality from stock returns to the sentiment index.
Test 2: H_0: Granger-noncausality from sentiment index to stock returns.

Variable definitions:
SENT: UK market sentiment; **SENT^P**: UK institutional sentiment; **AAII**: American Association of Individual Investors index; **II**: American Investors Intelligence index; **GMI**: German equity sentiment index; **BWSI**: Baker & Wurgler sentiment index, i.e. US market sentiment index. R_{big}: return on the large-size stock portfolio; R_{mid}: return on mid-size stock portfolio; R_{small}: return on small-size stock portfolio.The data are monthly and cover the period 1st January 1996 to 30th June 2011. Exceptionally the *BWSI* is available only to December 2010

***Significant at 1% level; **Significant at 5% level; *Significant at 10% level.

Panel A: Correlation tests

	R_{big}	R_{mid}	R_{sml}
SENT	0.1014	0.1596**	0.2178**
SENT^P	0.0194	-0.0175	-0.0118
AAII	0.3176***	0.3316***	0.3287***
II	0.32897***	0.4133***	0.4028***
GMI	0.1247*	0.1139	0.1796**
BWSI	-0.1411*	-0.1773**	-0.1944***

Panel B: Granger causality tests

	R_{big}		R_{mid}		R_{sml}	
	Test 1	**Test 2**	**Test 1**	**Test 2**	**Test 1**	**Test 2**
SENT	<0.0001	0.2777	<0.0001	0.7314	<0.0001	0.8549
SENT^P	<0.0001	0.6361	<0.0001	0.9259	<0.0001	0.6491
AAII	0.5524	0.6664	0.9633	0.2477	0.8752	0.0834
II	0.0022	0.0436	0.0201	0.1823	0.0576	0.5223
GMI	<0.0001	0.2756	<0.0001	0.9090	0.0003	0.8836
BWSI	0.2593	0.2120	0.3078	0.1245	0.2789	0.1543

For small stocks, the test of null of AAII cannot cause R_{sml} cannot be rejected at the 5% level, indicating that prices of small stock are led by US individual sentiment, however, the null is rejected at the 10% level, suggesting it is still highly possible that returns of small stock are Granger caused by US individual sentiment. Similar to medium-size stocks, returns of small stocks have some impact on US institutional sentiment and UK and European investor sentiments but not vice versa.

Finally, regressing returns on the US, UK and European sentiment indexes investigates the details about their ability to predict future returns. The estimations are run in two models because of the shorter sample period of $BWSI$. The models are:

Model 1:

$$R_t = \alpha_0 + \sum_{j=1}^{3} \alpha_j R_{t-j} + \sum_{i=0}^{3} \beta_i SENT_{t-i} + \sum_{i=0}^{3} \gamma_i SENT_{t-i}^{p} + \sum_{i=0}^{3} \delta_i AAII_{t-i} + \sum_{i=0}^{3} \theta_i II_{t-i} + \sum_{i=0}^{3} \vartheta_i GMI_{t-i} + \sum_{i=0}^{3} \varphi_i BWSI_{t-i} + \omega_t \tag{3.16}$$

Model 2:

$$R_t = \alpha_0 + \sum_{j=1}^{3} \alpha_j R_{t-j} + \sum_{i=0}^{3} \beta_i SENT_{t-i} + \sum_{i=0}^{3} \gamma_i SENT_{t-i}^{p} + \sum_{i=0}^{3} \delta_i AAII_{t-i} + \sum_{i=0}^{3} \theta_i II_{t-i} + \sum_{i=0}^{3} \vartheta_i GMI_{t-i} + \varepsilon_t \tag{3.17}$$

whereR_t is returns of large, medium, and small-size stock portfolio.

The estimated results are reported in Table 3.19A, Table 3.19B and Table 3.19C respectively. The majority of the coefficients of sentiment variables for the lagged terms are statistically insignificant; therefore, the models are simplified by deleting some of the lagged terms of variables. The standard error and AIC are all improved in the reconstructed models, suggesting they are parsimonious models.

For large stocks, the estimated coefficients from both models present almost the same results though they are estimated by slightly different sample data. The results demonstrate that US institutional sentiment in current and lagged have some explanatory power to returns. This confirms the suggestion from the Granger-causality test about returns of large stocks and US institutional sentiment, II. All the other estimated sentiment coefficients are not significant, indicating that they are unlikely to influence returns of large-size stocks. This is quite different from the estimation results in the weekly interval, which indicates that UK large stock returns are affected by both US institutional sentiment and US individual sentiment. The positive signs of II suggest sentiment impact is reversed afterwards in the following periods.

For medium stocks, estimated coefficients demonstrate that US institutional sentiment has a significant and relatively long term influence on returns of UK medium stocks. Coefficients of $SENT$, $AAII$, and GMI, are not significant, suggesting that UK market sentiment, US individual sentiment and European institutional sentiment may not affect UK medium stock returns. This is quite different from the estimated results from the weekly interval, which show that US individual sentiment has an influence on UK medium stock returns but UK institutional sentiment has no effect on medium stock returns. However, US institutional sentiment has the greatest degree of influence on UK medium stock returns amongst all the sentiment indexes in both investment intervals.

The significant current UK institutional sentiment in model 2 suggests that UK institutional sentiment also has an influence on UK medium stock returns. It is notable however, that the coefficient becomes insignificant to the returns in model 1 which includes US market sentiment in the regression. Instead, US market sentiment is one of the significant explanatory factors of the returns of UK medium stocks. From the analysis of UK institutional sentiment in the previous section (section 3.8.4), it shows that US market sentiment is one of the significant determining variables for UK institutional sentiment. This indicates that UK institutional sentiment is led by US market sentiment. Therefore, the influence that UK institutional sentiment has on returns is taken place via US market sentiment, i.e. the UK institutional sentiment effect on returns of UK medium stocks is 'Made in USA'.

For small-size stocks, the estimated results from both models present very similar pictures, though US market sentiment is included in model1 as an explanatory variable, which suggests that US market sentiment does not affect returns of UK small stocks. The strongly significant II_0, II_1, GMI_0 and GMI_1demonstrates that returns of small-size stocks are affected by US institutional sentiment and European institutional sentiment in their current and one period lagged term. In addition, the significance of $SENT_1^p$ and $SENT_2^p$ indicates that the one and two lagged UK institutional sentiment also has influence on returns of UK small stocks. The sign of the variable coefficients suggest a strong reverse effect of investor sentiment on returns.

The regression results exhibit the following features. Firstly, returns of all size stocks in the UK equity market are affected by US institutional sentiment. This means that US institutional sentiment has an impact on UK equity prices regardless the size different. Secondly, both UK market sentiment and US individual sentiment have no effect on UK stock returns regardless of stock sizes, i.e., UK market sentiment and US individual sentiment do not influence UK equity returns. Thirdly, whether UK institutional sentiment, European institutional sentiment, and US market sentiment have an impact on UK equity returns is dependent on the size of the stock. European Institutional sentiment has an impact on returns of UK medium and small stocks, US market sentiment influences returns of UK medium stocks, and UK institutional sentiment affects the returns of UK small stocks. Fourthly, among the three sizes of stocks, returns of small stocks are more likely to be affected by domestic and foreign investors' sentiment. Returns of large stocks are only influenced by US institutional sentiment. Finally, similarly to weekly frequency, reverse effect, i.e. the initial effect of investor sentiment reversing in the following periods, exists in all sizes of equities.

Table 3.21A: Regression analysis of monthly returns of large stocks (R_{big}) on sentiment indexes

Table 3.19A reports the results of estimating equations of the general form:

Model 1: $R_{size,t} = \alpha_0 + \sum_{j=1}^{3} R_{size,t-j} + \sum_{i=0}^{3} \beta_i SENT_{t-i} + \sum_{i=0}^{3} \gamma_i SENT_{t-i}^{p} + \sum_{i=0}^{3} \delta_i AAII_{t-i} + \sum_{i=0}^{3} \theta_i II_{t-i} + \sum_{i=0}^{3} \vartheta_i GMI_{t-i} + \sum_{i=0}^{3} \varphi_i BWSI_{t-i} + \varepsilon_t$

Model 2: $R_{size,t} = \alpha_0 + \sum_{j=1}^{3} R_{size,t-j} + \sum_{i=0}^{3} \beta_i SENT_{t-i} + \sum_{i=0}^{3} \gamma_i SENT_{t-i}^{p} + \sum_{i=0}^{3} \delta_i AAII_{t-i} + \sum_{i=0}^{3} \theta_i II_{t-i} + \sum_{i=0}^{3} \vartheta_i GMI_{t-i} + \varepsilon_t$

The estimation method is OLS with Newey-West standard errors. The data are monthly and cover the period 1st January 1996 to 30th June 2011. Exceptionally the *BWSI* is available only to December 2010

Variable definitions:

size = *big*, *mid* or *sml*; so, R_{big}: return on the large-size stock portfolio; R_{mid}: return on mid-size stock portfolio; R_{small}: return on small-size stock portfolio; $SENT$: UK market sentiment; $SENT^{p}$: UK institutional sentiment; **AAII**: American Association of Individual Investors index; **II**: American Investors Intelligence index; **GMI**: German equity sentiment index. **BWSI**: Baker & Wurgler sentiment index, i.e. US market sentiment

***Significant at 1% level; **Significant at 5% level; *Significant at 10% level.

	Including BWSI (01/01/1996 - 31/12/2010)				Excluding BWSI (01/01/1996 - 30/06/2011)			
	Model 1		*Reconstructed model 1*		*Model 2*		*Reconstructed model 2*	
	Coef.	**t-Stat**	**Coef.**	**t-Stat**	**Coef.**	**t-Stat**	**Coef.**	**t-Stat**
Constant	-2.1804*	-1.7210	-1.1182	-1.4407	-2.4375***	-2.2303	-1.3362	-1.5991
$R_{big,t-1}$	-0.1145	-1.3841			-0.1093	-1.3682		
$R_{big,t-2}$	-0.0683	-0.6843			-0.0511	-0.5353		
$R_{big,t-3}$	0.0056	0.0642			0.0020	0.0242		
$SENT_t$	0.0304	0.4824	0.0146	0.4224	0.0373	0.6255	0.0212	0.6299
$SENT_{t-1}$	-0.0142	-0.1671			-0.0162	-0.2019		
$SENT_{t-2}$	0.0080	0.1215			0.0085	0.1320		
$SENT_{t-3}$	0.0147	0.3301			0.0203	0.4791		
$SENT^P_t$	0.0119	0.0101	0.4558	0.6037	-0.0457	-0.0390	0.3050	0.4907
$SENT^P_{t-1}$	0.7619	0.4959			0.6713	0.4530		
$SENT^P_{t-2}$	-1.6784	-0.9879			-1.4414	-0.8617		
$SENT^P_{t-3}$	1.5275	1.0506			1.1374	0.8818		
$AAII_t$	0.0303	1.3806	0.0261	1.5653	0.0269	1.4109	0.0198	1.1617
$AAII_{t-1}$	0.0097	0.5501			0.0023	0.1393		
$AAII_{t-2}$	-0.0057	-0.2874			-0.0081	-0.4506		
$AAII_{t-3}$	-0.0013	-0.0659			-0.0089	-0.5313		
II_t	0.2161***	5.1994	0.2008***	6.0538	0.2187***	5.7461	0.2100***	5.8856
II_{t-1}	-0.2067***	-4.6631	-0.1919***	-5.8431	-0.1967***	-4.4826	-0.1922***	-6.8558
II_{t-2}	-0.0071	-0.1200			-0.0067	-0.1143		
II_{t-3}	0.0313	0.6539			0.0371	0.7882		
GMI_t	0.0330	0.7825	0.0103	1.2394	0.0402	0.9254	0.0107	1.1488
GMI_{t-1}	-0.0262	-0.3096			-0.0413	-0.5034		
GMI_{t-2}	-0.0039	-0.0580			0.0102	0.1572		
GMI_{t-3}	0.0065	0.1827			0.0019	0.0551		
$BWSI_t$	-2.0388	-0.7298	-0.7343	-1.5458				
$BWSI_{t-1}$	3.0373	0.8766						
$BWSI_{t-2}$	-1.4532	-0.4208						
$BWSI_{t-3}$	-0.4529	-0.1676						
Adj. R^2	0.2513		0.2821		0.2558		0.2765	
S.E.	3.7707		3.6686		3.7056		3.6312	
AIC	5.6381		5.4814		5.5805		5.4543	
LM test	1.9668**		1.5719		2.0997**		1.6971*	
ARCH	2.0574		1.4622		1.6935		1.3281	

Table 3.19B: Regression analysis of monthly returns of medium stocks ($\mathbf{R_{mid}}$) on sentiment indexes

Table 3.19B reports the results of estimating equations of the general form:

Model 1: $R_{size,t} = \alpha_0 + \sum_{j=1}^{3} R_{size,t-j} + \sum_{i=0}^{3} \beta_i SENT_{t-i} + \sum_{i=0}^{3} \gamma_i SENT_{t-i}^{p} + \sum_{i=0}^{3} \delta_i AAII_{t-i} + \sum_{i=0}^{3} \theta_i II_{t-i} + \sum_{i=0}^{3} \vartheta_i GMI_{t-i} + \sum_{i=0}^{3} \varphi_i BWSI_{t-i} + \varepsilon_t$

Model 2: $R_{size,t} = \alpha_0 + \sum_{j=1}^{3} R_{size,t-j} + \sum_{i=0}^{3} \beta_i SENT_{t-i} + \sum_{i=0}^{3} \gamma_i SENT_{t-i}^{p} + \sum_{i=0}^{3} \delta_i AAII_{t-i} + \sum_{i=0}^{3} \theta_i II_{t-i} + \sum_{i=0}^{3} \vartheta_i GMI_{t-i} + \varepsilon_t$

The estimation method is OLS with Newey-West standard errors. The data are monthly and cover the period 1st January 1996 to 30th June 2011. Exceptionally the *BWSI* is available only to December 2010

Variable definitions:

size = *big*, *mid* or *sml*; so, R_{big}: return on the large-size stock portfolio; R_{mid}: return on mid-size stock portfolio; R_{small}: return on small-size stock portfolio; $SENT$: UK market sentiment; $SENT^p$: UK institutional sentiment; **AAII**: American Association of Individual Investors index; **II**: American Investors Intelligence index; **GMI**: German equity sentiment index. **BWSI**: Baker & Wurgler sentiment index, i.e. US market sentiment.

***Significant at 1% level; **Significant at 5% level; *Significant at 10% level.

	Including BWSI (01/01/1996 - 31/12/2010)				Excluding BWSI (01/01/1996 - 30/06/2011)			
	Model 1		*Reconstructed model 1*		*Model 2*		*Reconstructed model 2*	
	Coef.	**t-Stat**	**Coef.**	**t-Stat**	**Coef.**	**t-Stat**	**Coef.**	**t-Stat**
Constant	-0.7740	-0.4370	-1.1018	-0.6800	-1.4603	-0.8405	-1.4637	-1.5992
$R_{mid,t-1}$	-0.0005	-0.0060			0.0058	0.0726		
$R_{mid,t-2}$	-0.1214	-1.4669			-0.0970	-1.1914		
$R_{mid,t-3}$	0.0653	0.7205			0.0774	0.9071		
$SENT_t$	0.0457	0.6906	0.0363	0.7314	0.0539	0.8672	0.0497	1.2350
$SENT_{t-1}$	-0.0078	-0.0892			-0.0084	-0.1015		
$SENT_{t-2}$	0.0351	0.4519			0.0303	0.4048		
$SENT_{t-3}$	-0.0557	-0.9479			-0.0352	-0.6286		
$SENT^P_t$	-0.6149	-0.4798	-1.3577	-1.4033	-0.6871	-0.5919	-1.5488*	-1.6573
$SENT^P_{t-1}$	0.9342	0.5536			1.0798	0.6234		
$SENT^P_{t-2}$	-2.2326	-1.1124			-2.1814	-1.0785		
$SENT^P_{t-3}$	0.9549	0.6630			0.5747	0.4137		
$AAII_t$	0.0390	1.7017	0.0266	1.1798	0.0330	1.5455	0.0182	0.9294
$AAII_{t-1}$	0.0168	0.8349			0.0085	0.4359		
$AAII_{t-2}$	0.0116	0.5190			0.0032	0.1570		
$AAII_{t-3}$	-0.0235	-1.1160			-0.0315	-1.6688		
II_t	0.2478***	4.3931	0.2536***	4.5918	0.2571***	4.9358	0.2649***	6.7144
II_{t-1}	-0.1838***	-3.4411	-0.1586***	-3.4682	-0.1860***	-3.6154	-0.1619***	-3.5566
II_{t-2}	-0.0507	-0.8419	-0.0646*	-1.6687	-0.0410	-0.7278	-0.0642	-1.4873
II_{t-3}	0.0882*	1.9620	0.0883**	2.1203	0.0925**	2.0287	0.0859**	2.3919
GMI_t	0.0837	1.6485	0.0036	0.3090	0.0879*	1.7410	0.0049	0.4899
GMI_{t-1}	-0.1031	-1.0601			-0.1083	-1.1733		
GMI_{t-2}	0.0431	0.4976			0.0349	0.4227		
GMI_{t-3}	-0.0241	-0.5051			-0.0106	-0.2332		
$BWSI_t$	-0.4614	-0.1747	-1.0717*	-1.8738				
$BWSI_{t-1}$	0.9611	0.2615						
$BWSI_{t-2}$	1.6505	0.3827						
$BWSI_{t-3}$	-3.3628	-1.1851						
Adj. R^2	0.3053		0.3080		0.3028		0.2989	
S.E.	4.4934		4.4687		4.4330		4.4316	
AIC	6.9883		5.8869		5.9390		5.8633	
LM test	1.4532		0.7808		1.1852		0.7391	
ARCH	6.5620***		2.6717*		3.4226**		2.1276	

Table 3.19C: Regression analysis of monthly returns of small stocks (R_{sml}) on sentiment indexes

Table 3.19C reports the results of estimating equations of the general form:

Model 1: $R_{size,t} = \alpha_0 + \sum_{j=1}^{3} R_{size,t-j} + \sum_{i=0}^{3} \beta_i SENT_{t-i} + \sum_{i=0}^{3} \gamma_i SENT_{t-i}^{p} + \sum_{i=0}^{3} \delta_i AAII_{t-i} + \sum_{i=0}^{3} \theta_i II_{t-i} + \sum_{i=0}^{3} \vartheta_i GMI_{t-i} + \sum_{i=0}^{3} \varphi_i BWSI_{t-i} + \varepsilon_t$

Model 2: $R_{size,t} = \alpha_0 + \sum_{j=1}^{3} R_{size,t-j} + \sum_{i=0}^{3} \beta_i SENT_{t-i} + \sum_{i=0}^{3} \gamma_i SENT_{t-i}^{p} + \sum_{i=0}^{3} \delta_i AAII_{t-i} + \sum_{i=0}^{3} \theta_i II_{t-i} + \sum_{i=0}^{3} \vartheta_i GMI_{t-i} + \varepsilon_t$

The estimation method is OLS with Newey-West standard errors. The data are monthly and cover the period 1st January 1996 to 30th June 2011. Exceptionally the *BWSI* is available only to December 2010

Variable definitions:

size = *big*, *mid* or *sml*; so, R_{big}: return on the large-size stock portfolio; R_{mid}: return on mid-size stock portfolio; R_{small}: return on small-size stock portfolio; $SENT$: UK market sentiment; $SENT^{p}$: UK institutional sentiment; **AAII**: American Association of Individual Investors index; **II**: American Investors Intelligence index; **GMI**: German equity sentiment index. **BWSI**: Baker & Wurgler sentiment index, i.e. US market sentiment

***Significant at 1% level; **Significant at 5% level; *Significant at 10% level.

	Including BWSI (01/01/1996 - 31/12/2010)				Excluding BWSI (01/01/1996 - 30/06/2011)			
	Model 1		*Reconstructed model 1*		*Model 2*		*Reconstructed model 2*	
	Coef.	t-Stat	Coef.	t-Stat	Coef.	t-Stat	Coef.	t-Stat
Constant	-1.0625	-0.5491	-1.8119	-1.4237	-1.9991	-1.4982	-2.1221*	-1.7544
$R_{mid,t-1}$	0.0474	0.5390	0.0797	0.9041	0.0799	0.8851	0.0934	1.0875
$R_{mid,t-2}$	-0.1476*	-1.9171	-0.1212	-1.3876	-0.1269	-1.4113	-0.1151	-1.3489
$R_{mid,t-3}$	0.0270	0.3208			0.0455	0.5149		
$SENT_t$	0.1167	1.4524	0.0863	1.1375	0.1130	1.5104	0.0992	1.3487
$SENT_{t-1}$	0.0121	0.1226	-0.0325	-0.4401	0.0189	0.2026	-0.0321	-0.4468
$SENT_{t-2}$	-0.0742	-0.8395			-0.0788	-0.8361		
$SENT_{t-3}$	-0.0394	-0.5260			-0.0106	-0.1480		
$SENT^{P}_{t}$	-1.0160	-0.6420	-1.6064	-0.9623	-1.1206	-0.6578	-1.8017	-1.1057
$SENT^{P}_{t-1}$	2.3223	1.3259	3.3949*	1.7406	2.6916	1.3730	3.2765*	1.7140
$SENT^{P}_{t-2}$	-3.6577*	-1.6830	-2.9441*	-1.7817	-3.4888*	-1.7726	-2.9835*	-1.8687
$SENT^{P}_{t-3}$	1.1334	0.6777			0.5668	0.3432		
$AAII_t$	0.0370	1.6146	0.0330	1.3194	0.0314	1.2598	0.0269	1.1254
$AAII_{t-1}$	0.0399*	1.8101	0.0355	1.4337	0.0266	1.0001	0.0242	1.0146
$AAII_{t-2}$	0.0119	0.4436			0.0000	-0.0010		
$AAII_{t-3}$	-0.0315	-1.3123			-0.0373	-1.5602		
II_t	0.2388***	3.5139	0.2265***	4.7718	0.2424***	5.2329	0.2378***	5.2714
II_{t-1}	-0.1985***	-3.5155	-0.1993***	-3.4594	-0.1981***	-3.4172	-0.1944***	-3.4509
II_{t-2}	-0.0329	-0.5371	-0.0109	-0.1986	-0.0132	-0.2163	-0.0119	-0.2203
II_{t-3}	0.0839*	1.7213	0.0597	1.3379	0.0839*	1.6599	0.0598	1.3679
GMI_t	0.1042**	1.9806	0.1080***	2.6220	0.1139**	2.3687	0.1083***	2.7650
GMI_{t-1}	-0.1096	-1.0569	-0.1007**	-2.4862	-0.1318	-1.5864	-0.0997**	-2.5898
GMI_{t-2}	0.0680	0.6496			0.0665	0.7959		
GMI_{t-3}	-0.0555	-0.8735			-0.0366	-0.7608		
$BWSI_t$	-0.8291	-0.2980	-1.1381	-0.3734				
$BWSI_{t-1}$	3.2072	0.8136	-0.2144	-0.0692				
$BWSI_{t-2}$	1.6030	0.3339						
$BWSI_{t-3}$	-5.4521	-1.5877						
Adj. R^2	0.3005		0.3041		0.2876		0.2836	
S.E.	5.0084		4.9842		4.9744		4.9433	
AIC	6.2058		6.1466		6.1694		6.1173	
LM test	1.7658*		1.4287		1.3355		1.2628	
ARCH	1.0922		0.6365		0.5073		0.4374	

3.11 Monthly investor sentiment and financial crisis

The sentiment effects in the crisis time are investigated by imposing the defined normal, pre and in-crisis period conditions. According to the estimation results in section 3.9, a regression model that includes one period lagged term is generally a better fit model for investigating the relationship between returns and investor sentiment. Before imposing the financial crisis condition, the relationship between UK stock returns and UK investor sentiment is explored by regression returns on the composed indexes, $SENT$ and $SENT^p$. The regression results are in Table 3.20 and it can be seen that both UK market and institutional sentiment have no effect on the returns on large and medium size stocks. For small size stocks, current market sentiment has a positive effect on returns and institutional sentiment cannot influence stock returns. The financial crisis conditions: non-crisis period, pre-crisis periods, and in-crisis periods conditions are imposed to investigate investor sentiment effect to stock returns in different crisis stages.

$$\begin{aligned} R_t = {} & \alpha_1^{no-cri} D_1 + \alpha_2^{no-cri} R_{t-1} * D_1 + \sum_{i=0}^{1} \beta_i^{no-cri} SENT_{t-i} * D_1 + \sum_{i=0}^{1} \gamma_i^{no-cri} SENT_{t-i}^{p} \\ & * D_1 + \alpha_1^{pre-cri} D_1 + \alpha_2^{pre-cri} R_{t-1} * D_2 + \sum_{i=0}^{1} \beta_i^{pre-cri} SENT_{t-i} * D_2 \\ & + \sum_{i=0}^{1} \gamma_i^{pre-cri} SENT_{t-i}^{p} * D_2 + \alpha_1^{in-cri} D_3 + \alpha_2^{in-cri} R_{t-1} * D_3 \\ & + \sum_{i=0}^{1} \beta_i^{in-cri} SENT_{t-i} * D_3 + \sum_{i=0}^{1} \gamma_i^{in-cri} SENT_{t-i}^{p} * D_3 + \varepsilon_t \end{aligned} \tag{3.18}$$

where R_t is return of the stock portfolio (either R_{big}, R_{mid}, or R_{sml}). $D_1 = 1$in non-crisis periods and zero otherwise; $D_2 = 1$ in pre-crisis periods and zero otherwise; $D_3 = 1$ for in-crisis periods and zero otherwise. The regression results are reported in Table 3.20.

For large stock, the coefficients of all sentiment variables are insignificant in the unconditional regression, suggesting that investor sentiment generally has little effect on returns. When imposed in crisis conditions, the coefficients of sentiment variables are insignificant in the normal time, which agrees with the unconditional regression. The significant of $SENT_0^{p,pre-cris}$ demonstrates that returns are affected by current institutional sentiment at pre-crisis period. All coefficients of sentiment variables are insignificant during non-crisis period and crisis period, suggesting that returns of large-size stocks may only be affected by institutional sentiment in the bubble building pre-crisis time. This may be an implication that institutional sentiment is one of the factors that contribute to the asset price bubble. Tests of asymmetric effect of investor sentiment suggest that the influence that institutional sentiment has on returns in the pre-crisis period is different from that in the normal time, however, the null of $SENT_0^{p,pre-cri} = SENT_0^{p,in-cris}$ cannot be rejected at the 10% significance level, suggesting a symmetric effect of institutional sentiment on returns of large stocks in pre- and in-crisis periods.

As with returns of medium stocks, the coefficients of all sentiment variables are insignificant in the unconditional regression, suggesting that investor sentiment generally has little effect on returns of medium stocks. When imposed in crisis conditions the coefficient of $SENT_1^{in-cri}$ is significant, demonstrating that lagged market sentiment has an impact to returns of medium stocks. All coefficients of sentiment variables are insignificant during normal and pre-crisis periods, suggesting that investor sentiment has little influence on returns of medium-size stocks in normal and pre-crisis time.

For small-size stocks, estimated coefficients suggest that current market sentiment is more likely to influence returns of small-size stocks in general in the unconditional regression, and market sentiment influences returns of small stocks is to a different degree from that of institutional sentiment influence on returns of small stocks. When the conditions are imposed, $SENT_0^{no-cri}$ is significant during normal time, which confirms the suggestions that come from the unconditional regression. No coefficients of sentiment variables during pre-crisis period are significant, implying that returns of small stocks are not affected by investor sentiment in this time. However, during financial crisis periods, lagged market sentiment has some explanatory power to returns of small stocks. This is very similar to returns of medium stocks. The tests of asymmetric effect of market sentiment in different crisis stages are rejected.

Among large, medium, and small stock portfolios, all coefficients of institutional sentiment variables are insignificant in normal and crisis time, and all coefficients of market sentiment variables are not significant during pre-crisis time. This suggests that institutional sentiment has very little influence on returns in normal and crisis time, and market sentiment has little effect on returns during pre-crisis period. The regression results also indicate that it is more likely that returns of large stocks are affected by institutional sentiment in the market unrest time, and returns of medium and small stocks are influenced by market sentiment. This is because the large stocks seem to be held and traded by institutional investors and the ownership and trading activities of medium and small stocks are more likely to spread between institutional and individual investors.

The tests of asymmetric effect of investor sentiment in pre- and in-crisis periods suggest that the effects on returns of stocks are symmetrical. Especially, for large stocks, the null is rejected at a high significance level, suggesting that returns of large stocks may be affected by institutional sentiment pre-crisis as well as in crisis period, and the degree can be the same.

Table 3.22: Regression of monthly returns on UK sentiment indexes under financial crisis conditions

Table 3.20 reports the results of regressions of the following form:

$$R_{size,t} = \alpha_1^{no-cri} D_1 + \alpha_2^{no-cri} R_{size,t-1} * D_1 + \sum_{i=0}^{2} \beta_i^{no-cri} SENT_{t-i} * D_1 + \sum_{i=0}^{2} \gamma_i^{no-cri} SENT_{t-i}^{p} * D_1 + \alpha_1^{pre-cri} D_2 + \alpha_2^{pre-cri} R_{t-1} * D_2 + \sum_{i=0}^{2} \beta_i^{pre-cri} SENT_{t-i} * D_2 + \sum_{i=0}^{2} \gamma_i^{pre-cri} SENT_{t-i}^{P} * D_2 + \alpha_1^{in-cri} D_3 + \alpha_2^{in-cri} R_{t-1} * D_3 + \sum_{i=0}^{2} \beta_i^{in-cri} SENT_{t-i} * D_3 + \sum_{i=0}^{2} \gamma_i^{in-cri} SENT_{t-i}^{p} * D_3 + \varepsilon_t$$

The estimation method is OLS with Newey-West standard errors. The data are monthly and cover the period 1st January 1996 to 30th June 2011.

Variable definitions:

size = *big*, *mid* or *sml*; so, $\boldsymbol{R_{big}}$: return on the large-size stock portfolio; $\boldsymbol{R_{mid}}$: return on mid-size stock portfolio; $\boldsymbol{R_{small}}$: return on small-size stock portfolio; **SENT**: UK market sentiment; $\mathbf{SENT^P}$: UK institutional sentiment. D_1 = 1 in non-crisis periods and zero otherwise; D_2 = 1 in pre-crisis periods and zero otherwise; D_3 = 1 in in-crisis periods and zero otherwise. The pre- and in-crisis periods are as defined in Appendix 2. The no-crisis periods consist of the remaining observations in the sample. t statistics are shown in parentheses. Fi, i = 1,…,5, are F tests for the quantitative effects of UK market sentiment and institutional sentiment: F1:$\beta_0 = \gamma_0$; F2: $\beta_1 = \gamma_1$; F3: $\gamma_0^{no-cri} = \gamma_0^{pre-cri}$; F4: $\gamma_0^{pre-cri} = \gamma_0^{in-cri}$; F5: $\beta_1^{no-cri} = \beta_1^{pre-cri}$; F6: $\beta_1^{pre-cri} = \beta_1^{in-cri}$; F7: $\beta_0^{no-cri} = \beta_0^{pre-cri}$. F8: $\beta_0^{pre-cri} = \beta_0^{in-cri}$

***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

	$\boldsymbol{R_{big}}$				$\boldsymbol{R_{mid}}$				$\boldsymbol{R_{sml}}$			
	Full period	**Normal period**	**pre-crisis period**	**in-crisis period**	**Full period**	**Normal period**	**pre-crisis period**	**in-crisis period**	**Full period**	**Normal period**	**pre-crisis period**	**in-crisis period**
$\boldsymbol{\alpha_1}$	-0.4926 (-0.4965)	-0.7622 (-0.7151)	3.9461 (1.1575)	7.8279** (2.0518)	0.2734 (0.2164)	0.5230 (0.3462)	3.7181* (1.7998)	6.9727** (2.3777)	-0.1439 (-0.0972)	0.1526 (0.0806)	3.3831 (1.5173)	6.3143** (2.3437)
$\boldsymbol{R_{t-1}}$	0.0554 (0.5881)	0.0306 (0.2721)	-0.4377 (-1.3589)	-0.0683 (-0.4022)	0.1557* (1.8261)	0.1383 (1.1191)	-0.0198 (-0.1405)	-0.1558 (-1.0802)	0.2198** (2.4846)	0.1616 (1.4591)	0.2414** (2.0926)	-0.0409 (-0.2477)
$\boldsymbol{SENT_t}$	0.0176 (0.2660)	0.0594 (0.6517)	0.0800 (0.7305)	-0.1584 (-1.0460)	0.0774 (1.0956)	0.1290 (1.2189)	0.0212 (0.2184)	-0.1099 (-0.6936)	0.1463* (1.7385)	0.2195* (1.8071)	0.0217 (0.2608)	0.0076 (0.0420)
$\boldsymbol{SENT_{t-1}}$	0.0267 (0.4232)	0.0450 (0.4936)	-0.1408 (-0.1408)	-0.1974 (-1.6107)	-0.0063 (-0.0884)	0.0235 (0.2135)	-0.0644 (-0.6580)	-0.2638* (-1.8175)	-0.0559 (-0.6383)	-0.0438 (-0.3359)	-0.0626 (-0.6077)	-0.3515** (-2.2185)
$\boldsymbol{SENT^P{}_t}$	-1.3383 (-1.1739)	-0.7289 (-0.5166)	-5.1585*** (-2.7687)	-3.5111 (-0.9853)	-2.1980 (-1.6221)	-2.8306 (1.3812)	-2.3850 (-0.9249)	-2.3342 (-0.9979)	-2.9464 (-1.6396)	-3.3896 (-1.2591)	-0.6990 (-0.2435)	-5.7085 (--1.4527)
$\boldsymbol{SENT^P{}_{t-1}}$	1.1781 (1.0219	-0.2413 (-0.1756)	4.5049 (1.6045)	1.2264 (0.4064)	0.9962 (0.7596)	0.1944 (0.0952)	1.3333 (0.5396)	0.7085 (0.3305)	1.3989 (0.8890)	0.2880 (0.1197)	-0.3826 (-0.1363)	3.0541 (1.1968)
F1		0.3100	7.6474***	0.8971		0.0067	0.3125	0.1939	2.8511*	1.7380	0.0607	2.0365
F2										0.0178	0.0127	1.6882
F3			3.5677*									
F4			0.1682									
F5							2.4505				2.2505	
F6							1.3134				2.5611	
F7											1.8238	
F8											0.9268	

3.12 **Monthly returns under different market sentiment conditions**

In this section, the impact that investor sentiment has on stock returns and investor herding is examined by investigating the possible asymmetric effect under high ($SENT_t > \overline{SENT}$) and low ($SENT_t < \overline{SENT}$) UK market sentiment conditions, where $\overline{SENT}$is mean of the composted market sentiment. As demonstrated in the previous, returns of UK stocks are most likely to be affected by US investors' sentiment, therefore the investigation of returns under different market sentiment conditions will be conducted by regression returns on UK and US sentiment indexes. The model is as follows:

$$\begin{aligned} R_{size,t} = {} & \alpha_1^{High} D_1 + \alpha_2^{High} R_{size,t-1} * D_1 + \sum_{i=0}^{1} \beta_i^{High} SENT_{t-i} * D_1 + \sum_{i=0}^{1} \gamma_i^{High} SENT_{t-i}^{p} * D_1 \\ & + \sum_{i=0}^{1} \delta_i^{High} AAII_{t-i} * D_1 + \sum_{i=0}^{1} \theta_i^{High} II_{t-i} * D_1 + \alpha_1^{Low} D_1 + \alpha_2^{Low} R_{size,t-1} \\ & * D_2 + \sum_{i=0}^{1} \beta_i^{Low} SENT_{t-i} * D_2 + \sum_{i=0}^{1} \gamma_i^{Low} SENT_{t-i}^{p} * D_2 \\ & + \sum_{i=0}^{1} \delta_i^{Low} AAII_{t-i} * D_2 + \sum_{i=0}^{1} \theta_i^{Low} II_{t-i} * D_2 + \varepsilon_t \end{aligned} \tag{3.19}$$

where R_t is return of the stock portfolio (either R_{big} , R_{mid} , or R_{sml}). $D_1 = 1$ when $SENT_t > \overline{SENT}$ and zero otherwise; $D_2 = 1$ when $SENT_t < \overline{SENT}$ and zero otherwise.

For large-size stocks (Table 3.21), the significant of coefficients of II_0^{high}, II_1^{high}, II_0^{low}, and II_1^{low}suggests that current and lagged US institutional sentiment influences returns of UK large stocks in both high and low UK market sentiment. The insignificant of coefficients of other sentiment variables indicates that in UK market and institution sentiment, and US individual sentiment have little impact on returns of UK large stocks, regardless of the condition of UK market sentiment. Tests of asymmetric effect of US institutional sentiment on returns of UK large stocks suggest that there is an asymmetric effect from US institutional sentiment on returns of UK large stocks under high and low market sentiment.

Table 3.23: Regression of returns of large stocks on UK and US sentiment indexes under different market sentiment conditions in monthly frequency

Table 3.21 reports the results of regressions of the following general form:

$$R_{size,t} = \alpha_1^{High} D_1 + \alpha_2^{High} R_{size,t-1} * D_1 + \sum_{i=0}^{1} \beta_i^{High} SENT_{t-i} * D_1 + \sum_{i=0}^{1} \gamma_i^{High} SENT_{t-i}^{p} * D_1 + \sum_{i=0}^{1} \delta_i^{High} AAII_{t-i} * D_1 + \sum_{i=0}^{1} \theta_i^{High} II_{t-i} * D_1 + \alpha_1^{Low} D_1 + \alpha_2^{Low} R_{size,t-1} * D_2 + \sum_{i=0}^{1} \beta_i^{Low} SENT_{t-i} * D_2 + \sum_{i=0}^{1} \gamma_i^{Low} SENT_{t-i}^{p} * D_2 + \sum_{i=0}^{1} \delta_i^{Low} AAII_{t-i} * D_2 + \sum_{i=0}^{1} \theta_i^{Low} II_{t-i} * D_2 + \varepsilon_t$$

Estimated by OLS with Newey-West HAC Standard Errors & Covariance. The data are monthly and cover the period 1st January 1996 to 30th June 2011.

Variable definitions:
size = *big*, *mid* or *sml*; so, R_{big}: return on the large-size stock portfolio; R_{mid}: return on mid-size stock portfolio; R_{small}: return on small-size stock portfolio; **SENT**: UK market sentiment; $\mathbf{SENT^P}$: UK institutional sentiment. $D_1 = 1$ when $SENT_t > \overline{SENT}$ and zero otherwise; $D_2 = 1$ when $SENT_t < \overline{SENT}$ and zero otherwise.
Fi, i = 1,…,5, are F tests for the asymmetric effects of UK market sentiment and institutional sentiment: in different market conditions. F1: $\delta_0 = \theta_0$. F2: $\delta_1 = \theta_1$. F3: $\theta_0^{high} = \theta_0^{Low}$; where θ_0^{high} is θ_0 when $SENT_t > \overline{SENT}$ and θ_0^{low} is θ_0 when $SENT_t < \overline{SENT}$. F4: $\theta_1^{high} = \theta_1^{low}$, where θ_1^{high} is θ_1 when $SENT_t > \overline{SENT}$ and θ_1^{low} is θ_1 when $SENT_t < \overline{SENT}$.

***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

	R_{big}		R_{mid}		R_{small}	
	$SENT_t > \overline{SENT}$	$SENT_t < \overline{SENT}$	$SENT_t > \overline{SENT}$	$SENT_t < \overline{SENT}$	$SENT_t > \overline{SENT}$	$SENT_t < \overline{SENT}$
α_0	2.9062 (1.1970)	-2.2601** (-2.2384)	0.8040 (0.3481)	-1.6951 (-0.8860)	1.3936 (0.5168)	-2.4195 (-1.1074)
R_{t-1}	-0.2643 (-1.6202)	-0.0024 (-0.0287)	0.1323 (1.3422)	-0.0174 (-0.1675)	0.3508*** (2.9249)	0.0502 (0.5767)
$SENT_t$	-0.0360 (-0.6259)	-0.0119 (-0.1148)	-0.0831 (-1.1307)	0.0780 (0.7210)	-0.0796 (-0.8592)	0.1565 (1.1986)
$SENT_{t-1}$	-0.0088 (-0.1404)	0.0518 (0.6553)	0.0500 (0.7447)	-0.0101 (-0.1111)	0.0502 (0.6098)	-0.1093 (-0.8935)
$SENT^P_t$	-2.1489 (-1.2171)	-0.1257 (-0.0866)	-2.7540 (-1.2422)	-0.5163 (-0.3343)	-2.9516 (-1.1211)	-1.7465 (-0.9157)
$SENT^P_{t-1}$	1.4409 (0.8868)	0.9265 (0.7826)	1.8829 (0.9679)	-0.2309 (-0.1308)	1.2907 (0.5783)	1.5030 (0.7439)
$AAII_t$	0.0116 (0.4881)	0.0212 (0.9291)	0.0164 (0.5800)	0.0079 (0.2941)	0.0253 (0.7682)	0.0051 (0.1755)
$AAII_{t-1}$	-0.0004 (-0.0154)	0.0055 (0.2601)	0.0137 (0.5431)	0.0207 (0.8158)	0.0052 (0.1974)	0.0471* (1.8558)
II_t	0.1460*** (3.0011)	0.2803*** (6.3227)	0.1931*** (3.2063)	0.3348*** (4.4892)	0.1287** (2.0690)	0.3276*** (3.7255)
II_{t-1}	-0.1298*** (-3.1893)	-0.2580*** (-6.2171)	-0.1037* (-1.7911)	-0.2705*** (-4.9133)	-0.0514 (-0.8542)	-0.2772*** (-4.3702)
F1	1.6723	0.0767	1.7362	0.3027	1.3361	1.2025
F2	0.9358	1.0022	1.0260	0.0005	0.2541	0.7660
F3	4.1459**		2.0942		3.1995*	
F4	4.5336**		4.1283**		6.2570**	
$Adj\text{-}R^2$	0.288981		0.2649		0.2673	
S.E.	3.609076		4.5377		5.0347	
AIC	5.5076		5.9656		6.1734	
LM test	1.2992		0.7412		1.6145*	
ARCH	4.3331**		2.4108*		0.2561	

There are several differences between the results from weekly and monthly frequencies. Estimated coefficients in weekly frequency indicate that US individual sentiment has an effect on the return of UK large stocks under both high and low market sentiment conditions. Coefficients in monthly frequency, however, do not display the same effect. Another difference is that UK market sentiment also affects returns of large stocks in weekly frequency when the market wide sentiment is high, while there is no effect on returns in the monthly frequency. Individual investors are more like change their sentiment quicker than institutional investor sentiment. The effect of this change on return appears as the reverse effect in a shorter time span. In weekly frequency, it shows that the effect of US individual sentiment reverses straightaway in the next period, but it takes a longer time for US institutional sentiment effect to reverse. The effect of US institutional sentiment is more likely to be persistent in the short term.

For returns of medium stocks (Table 3.21) estimated coefficients display very similar picture as returns of large stocks. Current and US institutional sentiment influences returns no matter whether the overall UK market sentiment is high or low. Coefficients of UK market and institutional sentiment, and US individual sentiment have little influence on returns of UK medium stocks under both high and low market sentiment conditions. Hypothesis tests suggest that US institutional sentiment may have an asymmetric effect on returns of UK medium stocks under high and low market sentiment.

For small stocks (Table 3.21), estimated coefficients suggest that returns of UK small stocks are only affected by current US institutional sentiment when UK market wide sentiment is high. When UK market wide sentiment is low, current and lagged US institutional sentiment, as well as lagged US individual sentiment have impact on returns of small stocks. However, US individual sentiment has a much less significant impact compared to US institutional sentiment. This is quite different from the estimated results from weekly regression. In weekly frequency, coefficients suggest that US individual sentiment has a persistent effect of returns of UK small stocks when market wide sentiment is high. When market sentiment is low, US individual still affects returns highly significantly; however, the effect is reversed immediately in the following week. This may be the reason that in the monthly regression, US individual affect is persistent but at a very low significance level, i.e. over a relatively long interval, US individual sentiment is not reversed completely. UK investor sentiment has little influence on returns of UK small stocks under both high and low market condition. The asymmetric effect tests indicate that US institutional sentiment has an asymmetric effect on returns of UK small stocks.

From the regressions of returns among all size of stocks, it shows that US institutional sentiment has some explanatory power on UK equity returns no matter whether UK market wide sentiment is high or low and the effects can be asymmetric under different market sentiment conditions. When market wide sentiment is low, returns of small stocks are affected by US individual sentiment. All size stocks are likely not to be affected by either UK market sentiment or UK institutional sentiment regardless of what the market sentiment condition is. This generally confirms the finding that UK investor sentiment has very little explanatory power over UK equities, and in many cases, the influence of UK investors' sentiment on returns is more likely to be via US investors' sentiment.

3.13 **Conclusion**

In this chapter, the effects of foreign and local investor sentiment on UK equity returns are investigated using both weekly and monthly data. First, a set of practical investor sentiment indices is constructed to make separate measures of UK market wide investor sentiment and UK institutional investor sentiment. Prior literature and available sentiment indices focus on the United States: very few sentiment indices have been constructed for UK investor sentiment. They based on the Baker and Wurger (2006) approach, and are on annual and weekly frequencies. The UK market wide investor sentiment composed in this paper, although not the first, is a more comprehensive one. Combining the approaches of Brown and Cliff (2004) and Baker and Wurger (2006), the index is constructed by including a wider range of investor sentiment proxies. Moreover, the UK institutional sentiment index is one of the very few composed indices which measure institutional investor sentiment and it is the first one for UK institutional sentiment.

Secondly, the composed UK investor sentiment measures are examined against US and European investor sentiment measures. This reveals that UK investor sentiment is heavily influenced by US and European investor sentiment. US individual and institutional sentiment, and European sentiment all have the power to predict UK market sentiment, and US institutional sentiment has a greater effect on UK market sentiment than does US individual sentiment. UK institutional sentiment, on the other hand co-moves with US investor sentiment, and it is also affected by European investor sentiment.

Thirdly, the impact of investor sentiment on asset returns segregated by stock size is examined. It shows that returns on portfolios based on different sizes of stock are affected by different groups of investor sentiment over different investment intervals. In the weekly interval, returns of stocks are influenced by US individual and institutional sentiments regardless of the size difference. Reverse effect appears as return reversal in the following periods after initial sentiment affects the return. The reversal effect of institutional sentiment takes a relatively longer time than individual sentiment has for large and medium stocks, but for returns of small stock, it is individual sentiment that takes a longer time to reverse. In the monthly interval, returns of large stocks are influenced by US institutional sentiment. Returns of medium stock returns are affected by both US institutional sentiment and European institutional sentiment. Returns of small size stocks are influenced by UK, US and European institutional sentiments. The direct impact of foreign investor sentiment on UK equity returns is studied, as a large proportion of UK equities are held by foreign investors, and we find that UK equity returns are influenced heavily by US investor sentiment and hardly at all by local investor sentiment. The sentiment impact across different financial crisis stages is also examined. The results demonstrate that price bubbles may to some degree be caused by investor sentiment, and that a financial crisis may be a process of price reversal back to the fundamental.

Sentiment effects on UK equity returns are also examined under different market sentiment conditions. The results show that in the weekly interval, returns of stocks can be affected by investor sentiment when market sentiment is generally high. Returns of large stocks are more likely to be influenced by UK market sentiment as well as US individual and institutional sentiment. Returns of medium and small stocks are largely influenced by US individual and institutional sentiment. The effects US individual sentiment on UK equity returns are asymmetric and it appears that individual sentiment has a greater impact on returns when market sentiment is low. In the monthly interval, US institutional sentiment has some explanatory power on UK equity returns no matter whether UK market wide sentiment is high or low. The effects can be asymmetric for large and small stocks. When market wide sentiment is low, returns of small stocks are affected by US individual sentiment.

Chapter 4 Institutional Investor Herding

4.1 Introduction

Herding is typically described as a behavioural tendency for an individual to follow the actions of others. It can be defined as '…the phenomenon of individuals deciding to follow others and imitating group behaviours rather than deciding independently and atomistically on the basis of their own, private information.' (Baddeley, 2010, p282). The experimental evidence in social psychology suggests that individuals always abide by the group decision even when they perceive the group to be wrong (Sherif and Murphy (1936); Trade and Parsons (1903)). Investors, much like every human being, dwell in societies amongst other people with whom they interact. By observing other market participants, they may agree with the course of action from observation and choose to follow it. This convergence of opinions combined with convergence in trades leads to investor herd behaviour.

Bikhchandani and Sharma (2001) suggested that herding can be either a rational or irrational form of investor behaviour. Rational form of herding is generated by using information about other's actions and making sequential decisions following Bayes' rule. It is fostered by information cascades, reputation concerns and compensation structures. Baddeley (2010) argues that the outcome generated by Bayesian models can be good or bad depending on whether the actions of predecessors send down the correct or incorrect track. The learning from other's actions involves a cognitive process of information. The reputation concerns of herding corresponds what Keynes (1936) observed '…it is better to be conventionally wrong than unconventionally right' (Baddeley, 2010, p282). Hirshleifer and Teoh (2003) also point out that theoretical work on herding behavioural indicates that some irrational phenomena can actually arise very naturally in a fully rational setting. Irrational herding, on the other hand, is suggested as an outcome of a process which sociological, psychological and emotional factors are given a role in the decision making.

An investor is influenced by others in investments decisions and financial transactions. Such influence may be entirely rational, and it can be irrational perhaps due to a 'herd instinct' in the investor's decision-making, or an emotional response to information.

Financial markets are highly active and competitive. Market participants trade based on their own perceptions of risks and opportunities, the expected prices, and predicted returns. The price of securities is believed to be affected by the interactions of the trading activities of investors who hold heterogeneous beliefs, preferences, and trading strategies. When rational arbitrageurs meet bounded rational or irrational noise traders in the market, they trade on the fundamental information, simultaneously adjusting their trading strategies to react to other market participants. The unpredictable nature of noise traders' sentiment may stretch the mispricing further after arbitrageurs bet against the mispricing, and such risk can stop rational traders taking the opposite position against the noise traders to correct the mispricing. Rather, they may take the position in the same direction as sentiment investors, which could result in persistent mispricing staying unadjusted.

Welch (2000) pointed out that the incentives for investors to adopt herd behaviour can be varied. Utility interaction, sanction on deviants, positive payoff externalities, informational externalities, principal-agent payoff externalities, and irrational agent behaviour are typically theories that show the incentive to adopt herd behaviour. However, in the empirical applications, it is very difficult to discriminate such fine differences between the theories. Therefore the empirical studies focus on whether similar investment decisions are taking place in financial markets rather than test a particular theory.

4.2 Herding Theories

Herd behaviour in financial markets is often interpreted as investors chasing the trends and fads of the markets and trading on the same side of the market at a certain time. The academic literature is rich in models outlining the rationale of herding, information cascades, or feedback trading. According to the forces that drive investors into herding, the mechanisms can be generally summarised as: information difference, principal-agent relationship and investors' sentiment.

Information-driven herding behaviour, 'informational externalities' in Welch (2000), occurs because investors believe that 'others' may have some important information about the returns and this is revealed by their actions (Banerjee, 1992; Bikhchandani et al., 1992; and Shiller, 1995). Investors face similar investment decisions under uncertainty. Each of them has private information about the correct course of action, but the private information is not observable. Individual investors, therefore, observe each other's actions in conjecturing the return information or signal which may be useful. Herding behaviour arises in this setting. Under such circumstances herd behaviour is the outcome of information inefficiency rather than the incentive problems inherent in the principal-agent relationship.

Principal-agent relationship based herding behaviour, referred to as 'principal-agent payoff externalities' in Welch (2000), is relevant for professionals as a result of the incentives provided by the compensation scheme or in order to maintain their reputation. The professionals are fund managers who make investments on behalf of others or analysts who provide analytical information to investors. The uncertainties about the stock picking skill and portfolio managing ability of investment managers raise concerns from both the investors and the money managers. The reward scheme and terms of employment provide the incentives of the agents to imitate (Scharfstein & Stein, 1990; Trueman, 1994; Graham, 1999; Brennan, 1990; Zwiebel, 1995; and Maug & Naik, 1996).

On one hand, the ability of fund managers to pick the 'right' stocks (or analysts' recommendation), is always assessed by confirming the portfolio with other investment professionals. The manager will be considered as high ability if they have picked similar stocks as others. This encourages managers to form investment portfolios by imitating others rather than according to their own information (Bikhchandani & Sharma, 2001). Under such a mechanism, Scharfstein & Stein (1990) developed a 'learning' model in which managers herd on the investment decisions of others with the incentive of manipulating the labour market's inference regarding their own ability.

On the other hand, having learnt about the ability of the managers, investors update their beliefs and take appropriate action in which relative performance evaluation is introduced. It is believed to be optimal for the principal (i.e. employer of the investment manager) to write a relative performance contract to maximise a weighted sum of the principal's and the agent's utility. When the compensation of the investment manager depends on his/her investment performance compared with that of other similar professionals, investment managers tend to ignore their own information and "go with the flow" (Maug & Naik, 1996). In their models, Maug and Naik (1996) consider a risk-averse agent investor whose compensation depends on the performance of his/her own investment portfolio relative to the performance of a benchmark. The benchmark can be the performance of a separate group of investors or the return of an appropriate index. When both the agent and the benchmark have imperfect private information about asset returns, information inefficiency can be one of the reasons for the agent to imitate the benchmark in that his/her optimal investment portfolio moves closer to the benchmark's after observing the benchmark's actions. The relative performance compensation contract provides additional incentives for an agent to imitate the benchmark. The fact that the investment manager's compensation will decrease if the investment portfolio underperforms the benchmark would cause the agent to skew the investments even more closely towards the benchmark's portfolio.

Reputational considerations are also relevant to agency-concerns as they may lead to professional herd behaviour. A professional with a strong reputation has an incentive to imitate others in order preserve his/her reputation and the one with a weak reputation may use herding as a means of free riding on the reputation of better-reputed peers. Therefore professionals tend to exhibit similarities by adhering to the line of the 'opinion leaders' or the perceived majority. Trueman (1994) reveals that analysts release forecasts similar to those previously announced by other analysts, even when this is not justified by their own information. Welch (2000) points out that an analyst's recommendations revision has a significant positive influence on the next two analyst's revisions, especially when short-run ex-post stock returns are accurately predicted by the revision and if the most recent revision has occurred more recently, the influence is even stronger.

The sentiment based approach demonstrates the mechanism of intentional herding behaviour by individuals who are not fully rational. Papers include Delong et al. (1990), Froot et al. (1992), Hirshleifer et al. (1994), Grinblatt et al. (1995) and Lux & Marchesi (1999). They model herd behaviour under two basic noise trader theory assumptions: (i) some investors are sentiment driven (i.e. not fully rational); (ii) arbitrage is risky and hence limited. Froot, Scharfstein, and Stein (1992), FSS henceforth, show that investors have exogenous short horizons and seek information held by other traders. They may ignore information about the fundamental value of the asset and herd on a subset of information because information spillover is positive in the short-horizon. This means that when fundamental information has not been incorporated into prices, a trader is made better off by trading on the same information as others. The model illustrates that the marginal return from trading increases when speculators liquidate their holding before the fundamental information is realized because more news about the same part of fundamental information that the speculators trade on is priced in the market.

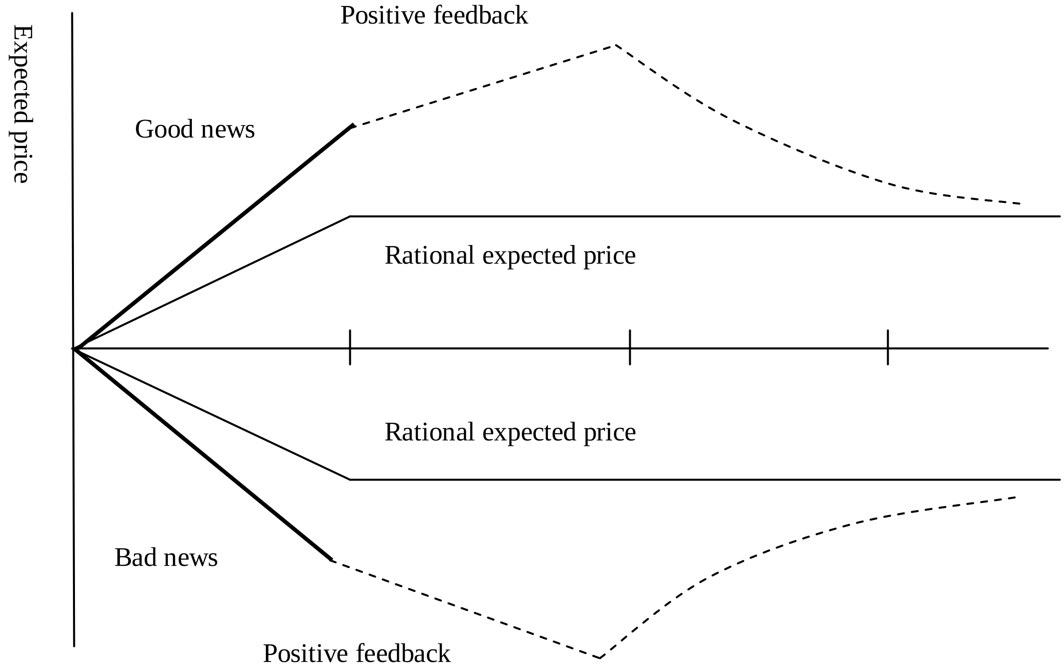
Instead of timing market liquidity as in FSS model, Hirshleifer et al. (1994) assume that private information is received either early or later by investors. The sequential nature of arrival of private information has a significant effect on both the trading decisions and the types of information being collected. The model suggests that the trades of early-informed traders are positively correlated with the private information before it arrives to the late-informed traders, and negatively correlated after it arrives to the late-informed traders. The trades of the late-informed traders are positively correlated with the previous period trades of the early-informed traders, and the risky asset price moves are positively correlated with the private information. These indicate that the early-informed traders can make a profit by reversing their position when late-informed traders start to trade on the same information and it becomes more pronounced as the proportion of late-informed traders increases.

4.3 Positive feedback models

The time-variation of information and market liquidity also implies that investors can sometimes profit by herding on private information or noise traders' systematic sentiment. DeLong et al. (1990) demonstrate that speculative investors tacitly coordinate their trades based on anticipating the positive feedback trader trades of noise investors. Positive feedback traders tend to chase the price trends, they buy securities when prices rise and sell when they fall (i.e. momentum).

As shown in Figure 4.1, in anticipation of such price herd behaviour, speculators buy more today, reflecting good news, and so drive prices up higher. Positive feedback traders, then buy the securities in response to the price increase. This may keep the price above fundamentals even as speculators sell out the securities and make profit. The speculators betting on positive feedback traders' trend chasing behaviour rather than the asset fundamentals, leads the price change in response to the news to be temporarily greater than the news warranted, i.e. the price overreacts to the news and deviates from the fundamentals. By taking advantage of the short-horizon extrapolation of positive feedback traders, speculators can increase their overall profits, and drive the asset price away from its fundamental value.

Figure 4.1[26]: Price effect with positive feedback traders.



This figure shows that anticipating feedback traders' price trend tracing strategy, speculators overreact to the news and push the price away from its fundamental level.

Boco, Germain, & Rousseau (2010) further introduce informed overconfident traders into DeLong et al., (1990)'s model to look at how overconfident traders exploit the presence of feedback traders. Consistent with DeLong at al., (1990), the four period model shows that in the presence of positive feedback traders, neither rational informed nor overconfident informed traders can stabilise security prices while they exploit the positive feedback trader's present in the market. The model also indicates that the main source of excess volatility is due to the trading from feedback traders rather than that of overconfident traders. The excess volatility depends critically on the number of feedback traders in the market.

[2] Source of original: Daniel, Hirshleifer & Subrahmanyam (1998), page 1847

4.4 Herding: Empirical Evidence

In the market setting, herding behaviours are characterised by investors suppressing their own beliefs and basing their investment decisions solely on the collective actions of the market, even if they disagree with them. This can be an investment strategy based on mimicking other market participants' actions or the market consensus. The consequences of herd behaviour will be reflected either in an aggregate level in asset returns or a micro level in investors' accounts, or both.

The return-base suggests that herd behaviour reflects on returns in that the individual stock returns tend to cluster around the average market return. Thus, examining the cross-sectional dispersion of returns can detect herd behaviour in the markets. In this level, herding is measured in two ways: one is the dispersion of individual asset returns to those of the overall market portfolio; the other is the deviation of the asset biases' betas from the CAPM betas. Cross section dispersion measures are generally used as the media to examine herding behaviour in the market which can be referred to as indirect measures. They focus on the price implication of herding is based on financial theories. Stock returns data is widely available and in higher frequencies such as daily and weekly. The links between theories and the measures, however, can be quite weak and subject to different interpretations. They generally measure the collective behaviour of all participants in the markets and do not discriminate between one group of investors and the other.

The micro-level of herding investigation is based on the assumption that herding investors trade on the same stock (or same group of stocks) in the same direction at the same period. Therefore, examining trade order imbalance is used to detect herd behaviour directly by measuring the number of buyers and sellers active or the monetary value of the trades during a given period. These measures enable the investigation of herd behaviour by groups, such as institutional and individual investors. Stock fundamentals are likely to cause investors to buy or sell the same stock (group of stocks) at the same time which may generate significant order imbalance and be presented as herding evidence. It is, therefore, difficult to distinguish the source of herding by this measure. The measure also needs detailed investors' trading or holding data which, in practice, is limited in availability and perhaps in very low frequency, such as quarterly and/or half –year data.

4.4.1. Return-based herding

Christie and Huang (1995) (CH) use daily and monthly data to test for herd behaviour at the industry-level as well as at aggregate market level in the US. The extreme returns are defined as those lying one or five percent standard deviations from the period's (1962-1988 for daily and 1925-1988 for monthly) market-mean. Using the linear model framework presented later, CH document an absence of herd behaviour, as the cross-sectional dispersion of stocks was found to be increasing irrespective of the extreme returns being positive or negative. However, the increase in dispersion was found to be greater during extreme up versus extreme down market periods, indicating perhaps a sign of herd behaviour during the extreme down market periods.

Chang, Cheng, and Khorana (2000) (CCK) utilised the modified model incorporating the nonlinearities and asymmetry of direction to test for the presence of herd behaviours in US, Hong Kong, Japan, South Korea, and Taiwan equity markets. The results are mixed. Similarly to CH, they document an absence of herding in the US equity market. Neither did the Hong Kong market display investors herding behaviour. However, partial evidence of herding in Japan was documented and significant proof of herding in the two emerging markets, South Korea and Taiwan. Much like CH, CCK also found a higher rate of increase in the cross-sectional returns' dispersion during up- versus down-market.

Using daily price series of thirteen commodity futures contracts traded on three European exchanges, Gleason, Lee and Mathur (2003) employ CH method to document the absence of herd behaviour, and the cross-section return dispersion appears more uniform during extreme up periods compared to extreme down periods. Gleason, Mathur and Peterson (2004) utilise intraday Exchange Traded Funds data and apply CH and CCK methods. They again cannot find evidence of herd behaviour during extreme markets and again, they find a higher rate of increase in the cross-section return dispersion during extreme up markets as opposed to extreme down ones.

Caporale, Economou, & Philippas (2008) utilise CH and CCK measures to examine daily, weekly and monthly returns of stocks traded in the Athens Stock Exchange. They document the absence of herd behaviour during extreme market period, but evidence of herding over the whole sample period (1998-2007) for all three time intervals. Their findings also indicate that herding is stronger during periods of a rising market versus falling one.

Hwang and Salmon’s (2004) (HS) empirical studies of US and South Korean markets document highly persistent herd behaviour in both markets. The results on the US market here are quite different from those of CH and CCK. At the same time, HS extend the investigation of herding towards other factors, such as, size (small minus big, SMB), value (book-to-market high minus low, HML), and factors of Fama and French (1993), and document factor herd behaviour in both the US and South Korean markets.

Demirer and Kutan (2006) use both individual firm and sector-level data to examine herd behaviour in Chinese stock markets by applying CH approach. They document the absence of herding during extreme markets, but their findings indicate a higher cross-sectional returns' dispersion during extreme up-markets in opposition to the extreme down-markets. Tan, Chiang, Mason & Nelling (2008), however, apply a CCK measure on Chinese dual-listed stocks and find the presence of herding behaviours in the Chinese markets. Their findings also indicate that herd behaviour is more pronounced in the rising markets.

Caparelli, D’Arcangelis and Cassuto (2004) apply the methods of CH, CCK and HS to test for herding on the COMIT index in Italy. Their studies generate fairly mixed results. The CH approach provides no evidence of herd behaviour during extreme periods, which is in line with Christie and Huang (1995), Chang, Cheng, and Khorana (2000), Gleason, Mathur and Peterson (2004), Caporale, Economou, & Philippas (2008) and Tan, Chiang, Mason & Nelling (2008). The findings indicate that cross-section return dispersion is higher in the extreme up-market versus extreme down-market. CCK approach, however, reveals that herding evidence has been found in both global sample and size-verified subsamples. The HS approach confirms the presence of herding behaviour in the market. Finally, Demirer, Kutan and Chen (2010) employ CH, CCK and HS methods to examine daily returns of stocks traded on the Taiwan Stock Exchange. They document the absence of herding in most sectors except the Electronics sector during market extreme periods. Their findings also indicate a non-linear and decreasing relation between return dispersion and the market return, suggesting herd behaviour in the market. The herding effect is more likely to be prominent during falling markets.

4.4.2. Micro-level accounts-based herding

In the micro-level, studies employ individual account data test for herd behaviour. Lakonishok, Shleifer, and Vishny (1992), LSV henceforth, propose the standard order imbalance measures, which are calculated based on the number of institutional buyers related to the number of institutional sellers of a given stock or industry group at the same time. They calculate the order imbalance for each stock-quarter in their 769 US equity funds sample during the 1985-1989 period and find an inverse relationship between fund herding and stock-size in US market; that is, that funds herd to a greater degree in smaller capitalisation stocks. Grinblatt, Timan and Warmers(1995) studies US mutual funds between 1974 and 1984 and finds very weak evidence of funds tending to buy and sell the same stocks at the same time. In the mean time, their investigations reveal that majority mutual funds tend to buy past ‘winners’ but do not systematically sell past ‘losers’. Wermers (1999) further examine 20 years (1975-1994) of U.S. mutual fund data and found a fairly low but slightly higher level herding than pension fund on average stocks.

Choe, Kho and Stulz (1999) and Hong and Yi (2006) also applied LSV measure and found various levels of herding in the Korean equity market by employing different frequencies of data: daily versus monthly. Choe et al (1999) show that foreign funds herd less during the Asian Crisis compared to the normal periods, while Hong and Yi (2006) find that the concurrent relation between the degree of the herding of fund managers and stock returns is positive from the buy side of trades and is negative from the sell side of trades. Wylie (2005) also found evidence of herding in U.K. equity mutual funds by testing through LSV measures. Positive-feedback trading was also tested by examining the relationship between the demand of a stock and the past performance of it, and the result shows some evidence of positive-feedback trading in small stocks, but not in large stocks. Barber, Odean, and Zhu (2009), on the other hand, extend the studies by employing eighteen years (1983-2001) US security markets and two brokerages data. They show that the imbalance of buyer and seller initiated small trades, suggesting strong herding by individual investors.

Return-based herding studies generate very mixed results. The method that measures herding via extreme market condition seems to point towards the absence of herding during extreme market periods and suggests that turbulent periods discourage herding.

This may be due to the lack of a definitive market direction as Hwang and Salmon (2004) explain. However, the relationship between return dispersion and market provides evidence of herding in financial markets. The results of the examination of dispersion of time varying beta appear particularly to indicate that herding exists in both emerging and developed markets. Micro-level account based herding investigations provide results indicating the existence of herding in markets amongst market participants, irrespective of their classification, more so in emerging capital markets.

4.4.3. Institutional herding VS Individual herding

In the global financial markets, institutional investors play an ever-increasing role. For example, the shares of common equities held by investment institutions in the US have increased from 32% to 68% of total market value from 1980 to 2007 (Lewellen (2009))[27], and in China increased from 5% to 48.7% between 2002 and 2007(BSR 2009)[28]. Whether institutional investors' decisions and subsequent trading strategies are rational or not has become a vital factor in studying financial market anomalies and puzzles.

Individual investors are expected to exhibit a greater tendency to herd than institutional investors, as they often have limited access to information due to the costs (both financial and non-financial) of gathering and processing information. It is prudent and perhaps even rational for individual investors to assume that others know more than they do and to make their trading decisions based on the actions of the crowd. Moreover, because of the lack of information picking and analysis skills, individual investors are more likely be attracted by attention catching information and be influenced by other people's opinions. Their investment decisions are made, more or less based on intuition, feeling and mood, and psychological biases may amplify existing herding intentions among individuals.

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[4]Sources come from quarterly 13F filings compiled by Thomson Financial.

[5]"Sustainable Investment on China 2009 Overview", and data sources come from CSRC, "China Capital Markets Development Report"

An alternative perspective is that herd behaviour is more likely to be in vogue among institutional investors, and the scale and scope of herding are greater than individual investors. There are several theoretical foundations leading to institutional investor herd behaviour. Firstly, in order to build or maintain reputation, institutional investors (i.e. fund managers) may herd in the crowd (Scharfstein and Stein, 1990; Trueman 1994). As discussed in section 4.2, principal-agent relationship promotes the incentive of institutional investors to mimic others' decisions and trading strategies. Secondly, institutional investors know more about each others' trades since they are able to allocate sufficient of resources to study the market and their peers, at the same time, their trades are more visible to others, due to the size of the trade volumes, and the disclosure of holding position which is required by regulation. They may infer information from the prior actions of peer group agents and herd as a result (Shiller and Pound, 1989; Banerjee, 1992; Bikhchandani et al., 1992). Thirdly, correlated private information, such as analysts' recommendations, are more likely to reach institutions than reach individuals. Institutional fund managers end up favouring the same indicator and trading on the same side of the market (Froot et al., 1992; Hirshleifer et al., 1994).

The above two hypotheses lead to two primary streams of empirical herding study. One stream concentrates on investigating individual investor herding. The other stream focuses on the behaviour of institutional investors. The studies for institutional herding primarily try to find herding evidence in the micro-level by measuring the imbalance in the number of buyers to sellers in one particular stock (or group stocks).

Empirically, evidence of herding by fund managers has been found in both developed equity markets, like the U.S, UK, and Japan, and emerging equity markets, such as Korea, Taiwan, and China (Lakonishok et al. (1992), Grinblatt et al (1995), Wermers (1999), Wylie (2005), Choe et al. (1999), Chang et al (2000) and Liao et al.(2011)). Lakonishok et al. (1992) find that the US pension funds herd in smaller stocks but herd much less in large stocks. Grinblatt, Timan and Warmers(1995) studies US mutual funds and find very weak evidence of funds herding on buying and selling of the same stocks. Wermers (1999) further find a fairly low but slightly higher level of herding than pension funds on average stocks. Choe et al. (1999) and Hong and Yi (2006) find various levels of herding in the Korean equity market and Wylie (2005) Agudo, Sarto and Vicente (2008) find herding in U.K. and Spanish equity funds respectively.

Claudio& Schmukler (2012) found evidence of institutional herding by studying Chile's pension funds.

Indeed, institutional investors often engage in transactions which are similar to other institutions. Hirshleifer et al. (1994) indicated that institutional investors tend to investigate and trade the same group of stocks, in other words, they buy or sell the same stocks at roughly the same time. With the increasing number and size of institutional investors involved, their transactions may have a significant impact on stock price, volatility and return (Campbell, Lettau and Xu, 2001; Bennett, Sias and Starks, 2003). Nofsinger and Sias (1999) investigated the relationship between stock returns and the fraction of shares held by institutional investors by applying US NYSE 20 year's data (1977-1996). They found that the stocks which institutional investors purchase subsequently outperform those they sell, and institutional herding is positively correlated with lag return and appears to be related to stock return momentum. There also appears to be a positive relationship between annual changes in institutional ownership and returns, which suggests that institutional investors engage in a greater level of positive feedback trading than individual investors, and their herding has a larger price impact.

Compared with institutional investors, individual investors often are referred to as ignorant and uninformed investors trading on sentiment. The information they are able to access is limited and they are more likely be influenced by other people's opinions, such as, brokerage house recommendations, popular market gurus and forecasters. Practically, individual investors are more likely to engage in irrational positive feedback trading because they extrapolate by past growth rates (Lakonishok, et al, 1994). Applying Australian data for the period 1991-2002, Jackson (2003) uses an order imbalance measure based on net flows into or out of the equity market to explore the patterns in the trades of investors both in aggregate market level and cross-sectional level. He found at both levels, systematic correlations hold for both the trade number and the trade volume of individual investors, and the relationship is consistent over the observation period, which provides evidence of the herding of individual investors. Barber, et al (2009) study results suggest strong herding by individual investors, who predominantly buy (or sell) the same stocks as each other during the same period. The study also shows that the stocks heavily bought by individual investors one week earn strong returns in the same and the subsequent week, and vice versa.

4.5 Methods to measure herding

Christie & Huang (1995) (CH henceforth) uses cross-sectional standard deviation (CSSD)[29] and cross-sectional absolute deviation (CSAD)[30] to quantify the dispersion of asset returns. The rationale of their model is that a rise in herding would be imprinted into a decline of dispersion of returns. CH also point out that a low dispersion can be contributed to by other factors, such as a lack of new information in the market. They suggested that herd behaviours are more likely to be present during market stress periods, i.e. the price movements are more extreme. They isolated the level of dispersion of equity returns, S_t, in the extreme tails of the distribution of market returns, using the time series model:

$$S_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \epsilon_t \tag{4.1}$$

$S_t$is CSSD or CSAD. D_t^LandD_t^U are dummy variable defined as follows: if the market return on day t lies in the extreme lower tail of the distribution, $D_t^L = 1$; otherwise it is equal to zero. If the market return on day t lies in the extreme upper tail of the distribution, $D_t^U = 1$; otherwise it is equal to zero. Statistically significant negative values of β_1 and β_2 indicate the presence of herd behaviour, and α denotes the average dispersion of the sample excluding the regions covered by the two dummy variables.

Chang, Cheng, and Khorana (2000), CCK henceforth, modified the Christie and Huang (1995) model to examine the relationship between CSAD and the market portfolio return, R_m, to study herd behaviour. Applying a conditional version of Black (1972) CAPM[31], they define the average Absolute Value of the Deviation (AVD) as:

$$AVD_{it} = |\beta_i - \beta_m| E(R_m - \gamma_0) \tag{4.2}$$

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[29] $\mathrm{CSSD} = \sqrt{\frac{\sum_{i=1}^{n}(r_i - \bar{r})^2}{n-1}}$, where r_i is the observed return on stock i, $\bar{r}$ is the cross-sectional average return of the portfolio, and n is the number of stocks in the portfolio.

[30] $\mathrm{CSAD} = \frac{\sum_{i=1}^{n}|r_i - \bar{r}|}{n}$, where r_i is the observed return on stock i, $\bar{r}$ is the cross-sectional average return of the portfolio, and n is the number of stocks in the portfolio.

[31] expected return of any asset, i, at time t is: $E_t(R_i) = \gamma_0 + \beta_i E(R_m - \gamma_0)$

$\gamma_0$is the return on zero-beta portfolio, β_i is the systematic risk of asset i, and β_m is the systematic risk of an equally-weighted market portfolio, i.e. $\beta_m = \frac{1}{n}\sum_{i=1}^{n}\beta_i$. The expected CSAD is:

$$ECSAD = \frac{1}{n}\sum_{i=1}^{n}|\beta_i - \beta_m|E(R_m - \gamma_0) \quad (4.3)$$

CSAD and R_m are then used as proxies for the unobservable expected CSAD and return of market portfolio respectively. The increasing and linear relation between dispersion and the market expected returns can be revealed by deriving first and second order differentiation[32].

The rational asset pricing models predict that dispersions are an increasing function of the market return and also the relation is linear. If individual participants tend to follow aggregate market behaviour then the linear and increasing relation between dispersion and market return will no longer hold. Therefore the model is:

$$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2\left(R_{m,t}\right)^2 + \varepsilon_t \quad (4.4)$$

Since CSAD is the absolute value of dispersion of return, the absolute term of market returns, $R_{m,t}$, are also used to examine the positive linear relation. The square power of $R_{m,t}$ examines the non-linear relation.

The modified model incorporates the possibility of nonlinearities in the market as well as directional asymmetry, i.e. different degree responses of herding in up- versus down markets:

$$CSAD_t^{UP} = \alpha + \gamma_1^{UP}|R_{m,t}^{UP}| + \gamma_2^{UP}\left(R_{m,t}^{UP}\right)^2 + \varepsilon_t \quad (4.5)$$

$$CSAD_t^{DOWN} = \alpha + \gamma_1^{DOWN}|R_{m,t}^{DOWN}| + \gamma_2^{DOWN}\left(R_{m,t}^{DOWN}\right)^2 + \varepsilon_t \quad (4.6)$$

$|R_{m,t}^{UP}|$ ($|R_{m,t}^{DOWN}|$) is the absolute value of an equally-weighted realised return of all available securities on day t, when market is up(down). The investors expected return would be a less than proportional increase (or decrease) in the CSAD measure if there

[32] First order differentiating equation 4.3: $\frac{\partial ECSAD}{\partial E(R_m)} = \frac{1}{n}\sum_{i=1}^{n}|\beta_i - \beta_m| > 0$. The second order differentiation of equation 4.3 is: $\frac{\partial^2 ECSAD}{\partial^2 E(R_m)} = 0$

is herd behaviour during market stress periods. The return dispersions will decrease or increase at a decreasing rate with an increase in market return if severe herding is present. During market stress periods, herd behaviour would result in a non-linear relation between CSAD and the average market return, and this will be captured by a negative and statically significant γ_2.

Hwang & Salmon (2004), (HS) on the other hand argue that neither the CH nor CCK method has included any device to control for movements in fundamentals, therefore, it is impossible to identify whether the causes for the decrease in return dispersions are herding behaviours or just the adjustment to fundamentals. They point out that the perception of risk return relationship of assets may be distorted if investors are influenced by behavioural biases, and it is possible that betas of the stocks will deviate from their equilibrium values. Thus beta of a stock does not remain constant but changes with the fluctuations of investors' sentiment. The cross-sectional dispersion of betas is expected to be smaller in the presence of herd behaviour. They then propose a method to test for herding on the basis of cross-sectional dispersion of the factor-sensitivity of assets.

A herding parameter, H_{mt}, which is based on the CAPM equilibrium risk-return relationship and is biased by investors herding towards the performance of the market portfolio, is introduced to capture herd behaviour present in markets. When herding exists in the conventional CAPM, the equilibrium relationship no longer holds and both the beta and the expected return will be biased. Therefore given the view of the market at time t, $E_t(r_{mt})$, the expected asset return following CAPM equilibrium will be:

$$E_t(r_{it}) = \beta_{imt} E_t(r_{mt}) \tag{4.7}$$

Where r_{it} is the return on asset i at time t, r_{mt} is the market return at time t, and β_{imt} is the systematic risk measure.

The biased expected asset return will be

$$E_t^b(r_{it}) = \beta_{imt}^b E_t(r_{mt}) \tag{4.8}$$

Where $E_t^b(r_{it})$ is the biased short run conditional expectation on the excess returns of asset i and β_{imt}^b is the market's biased beta of asset i at time t.

HS assume that when investors herd towards the return of market portfolio, instead of the equilibrium relationship equation (4.7), the following relationship holds:

$$\frac{E_t^b(r_{it})}{E_t(r_{mt})} = \beta_{imt}^b = \beta_{imt} - h_{mt}(\beta_{imt} - 1) \tag{4.9}$$

where h_{mt} is a latent herding parameter that changes over time. $h_{mt} = 1$suggests the individual assets move in the same direction with the same magnitude as the market portfolio, indicating a perfect herding, and $h_{mt} = 0$ indicating there is no herding, and the equilibrium CAPM applies. $0 < h_{mt} < 1$means that some degree of herding exists in the market.

The herding behaviour HS try to explore is market-wide rather than a single asset. Equation 4.9, therefore, is assumed to hold for all assets, and the cross-sectional mean of β_{imt}^b or β_{imt},is always 1. Standard deviation of β_{imt}^b is:

$$\begin{aligned} Std_c\left(\beta_{imt}^b\right) &= \sqrt{E_c((\beta_{imt} - h_{mt}(\beta_{mt} - 1) - 1)^2)} = \sqrt{E_c((\beta_{imt} - 1)^2)}(1 - h_{mt}) \\ &= Std_c(\beta_{imt})(1 - h_{mt}) \end{aligned}$$

where Std_c is standard deviation of the cross-section of β_{imt}^b or β_{imt}, and E_c is the cross-sectional expectation β_{imt}^b or β_{imt}.

In order to measure h_{mt}, HS establish the state space model by taking logarithms of the cross-sectional mean of β_{imt}^b, resulting in:

$$log\left[Std_c\left(\beta_{imt}^b\right)\right] = \mu_m + H_{mt} + v_{mt} \tag{4.10}$$

where$Std_c(\cdot)$ represent the cross-sectional standard deviation, $H_{mt} = log(1 - h_{mt})$, and $log[Std_c(\beta_{imt})] = \mu_m + v_{mt}$, where $\mu_m = E\big(\log\big(Std_c(\beta_{imt})\big)\big)$ and $v_{mt} \sim iid(0, \sigma_v^2)$. Assuming a mean zero AR(1) process, this gives:

$$H_{mt} = \phi_m H_{mt-1} + \eta_{mt} \tag{4.11}$$

where $\eta_{mt} \sim iid(0, \sigma_{m\eta}^2)$, and the model can be estimated using the Kalman filter. When $\sigma_{m\eta}^2 = 0$, the model becomes $log[Std_c(\beta_{imt}^b)] = \mu_m + v_{mt}$, which means no herding exists, indicating $H_{mt} = 0$ for all t. The existence of herding can be captured by a statistically significant value of $\sigma_{m\eta}^2$. HS also constructed alternative models which include other factors, such as market volatility and returns, size and book-to market factors, and macroeconomic variables.

4.6 Conclusion

Herding, in its simplest terms, is referred to as a group of investors trading in the same direction at a certain time. In its broader terms, investors are also identified as herding when they follow each other into or out of the same (or same group) of securities over same period of time (Sias, 2004). Information inefficiency is clarified as one of the drivers of investors herding behaviour. Observing others' actions to conjecture the private information they may have, investors mimic each other's behaviour. Principal-agent mechanism herding suggests that the separation of ownership and management of investment fund leads to professional investors herding behaviour. The reward scheme, term of employment, and measure of assessment promote incentives for fund managers to 'learn' the investment decisions of others. Noise trader theories assume that some investors are sentiment-driven in decision making. Sentiment investors may ignore fundamental information and only seek information held by others which leads to the investment decisions are made based on the same information as others. DeLong et al. (1990) and Boco et al. (2010) demonstrate the price effect with trend tracing positive feedback investors. They suggest that asset price is driven away from its fundamental value by speculators taking advantage of herding behaviour of positive feedback traders.

Empirically, there are two major methods used for investigating herding behaviour. One of the approaches is to examine the level of individual stock returns clustering around the average market return. Cross section of return dispersions are generally used as the media to measure herding behaviour in the market. The assumption of this approach is that if the positive linear relation between market return and the cross-section return dispersion, which is suggested by rational asset price model, no longer holds there is herding behaviour evidence in the market. Christie & Huang (1995) investigate herding behaviour under extreme market conditions and Chang, Cheng and

Khorana (2000) examine the possible negative linear or non-linear relation of return dispersion and the absolute market returns. Herding evidence in US and UK markets is hardly found by these methods, though mixture results are received from investigating the markets in other countries. Hwang & Salmon (2004), however, found persistent herding behaviour in both US and South Korean markets by examining the cross-section dispersion of systematic risk (beta) of stocks. These three methods are normally used for investigating herding behaviour in market level. They do not discriminate between one group of investors and the other, such as individual and institutional investors.

Given the leverage of institutional investors in capital markets and the potential for destabilisation-inducing herding on their behalf, institutional investors' behaviours attract ever-increasing interest for research from scholars and practicians. Weak evidence is found in the study of US and UK funds (Lakonishok, Shleifer & Vishny, 1992; Wermers, 1999; Wylie, 2005; and Barber, Odean & Zhu, 2009). The widely used method for investigating institutional herding behaviour is to examine herding behaviour at the micro-level which measures the imbalance of buying and selling a stock by institutional investors. The returns of institutional investor portfolios have hardly been examined for the purpose of studying institutional herding behaviour. Therefore, in the following chapters, institutional investor portfolio returns are going to be examined to investigate herding behaviour of UK institutional investors.

Chapter 5 Institutional portfolio herding

5.1 Introduction

Amongst the studies of investors' sentiment and behaviour, institutional investor sentiment and herding behaviour are also found in the markets. Evidence suggests that they have strong explanatory power over stock price and return. One of the popular views holds that institutional herding is primarily responsible for large price movements of individual stocks (e.g. Lakonishok et al. (1992)). According to Brown & Cliff (2004), institutional sentiment can be one of the sources of strong co-movement of stock returns. This also implies that except for agency problems, security characteristics, and the manner in which information is incorporated in the market, sentiment may be another force for institutional investors engaging in herd behaviour. This has already been suggested by Friedman (1984) and Dreman (1979).

Although a recent growing body of literature is devoted to institutional investor herding, extant studies take divergent paths. One of the paths depicts investor engagement in herding as a result of an irrational but systematic response to fads or sentiment. Another path suggests that herd behaviour in the market is a result of agency problems, security characteristics, and/or the manner in which information is disseminated in the market. One of the consequences of the principle-agent relationship is that agents are evaluated by comparing their investment performance to that of their peers or a benchmark. This can lead agents, such as fund managers, to suppress their own portfolio picking strategies and try to mimic the portfolio of a market 'winner' or a generally accepted market portfolio in order to keep their investment returns in line with at least the market average. There is also 'hidden index-tracking' – portfolio managers who charge for stock picking will largely track an index. Examining the portfolios of professional money managers is therefore one way to approach the study of institutional investors' herding behaviour. In the market-wide herding studies, the dispersions of individual asset returns (or betas) to the market portfolio returns are used to measure investors' herd behaviour in the equity markets. Similarly, the dispersions of individual fund returns (or betas) to those of the market (or a benchmark) portfolio can be used to measure the herd behaviour of fund managers.

In the following sections, investigation of herd behaviour of UK institutional investors is conducted by examining UK open-ended funds and closed-end funds separately. An open-ended fund is a collective investment scheme without restriction on issuing and redeeming shares, i.e. open-ended funds continuously selling fund shares to, and purchasing back fund shares from, investors. The prices of open-ended funds mirror the value of the fund's investments, i.e. the net asset value (NAV). The changes in NAV reflect the money manager's portfolio picking decisions and trade strategies. A closed-end fund, on contract, has a fixed number of shares and new shares are not created by managers to meet demand from investors. Investors can only purchase or sell the shares in the market. Closed-end funds usually raise capital by conducting an Initial Public Offering (IPO) of a fixed amount of shares, and the shares are traded on a stock exchange. Prices of shares are determined by the market and can be different from fund NAV.

5.2 Data Description and Summary statistics

In this section, 84 UK Unit trusts and Open-ended investment companies (OEICs) and 119 closed-end funds which are listed on the London Stock Exchange main market are selected to be used for examination of the herding behaviour of open-ended fund managers and closed-end fund managers respectively.

Among the 84 opened-funds, 74 of them mainly invest in large cap companies and 10 of them invest in mid-cap companies. The sample open-ended funds are equity focused funds whose investment holdings are concentrated on UK listed companies shares traded on the London Stock Exchange. The UK equity focused funds are qualified as such when there are more than 70% of holdings that are UK equities at the year of 2011. The 119 closed-end funds, on the other hand, are randomly selected without restriction of the trust investing in specific types of assets.

The UK mutual funds are selected for several reasons. Firstly, the UK equity market is dominated by institutional and foreign investors. According to the UK Office of National Statistics, by the end of 2010, institutional investors owned 47.3% of UK quoted shares, foreign investors owned 41.2%, and UK individuals owned 11.5% of the value of the UK stock market[33]. Therefore, fund managers' investment behaviour can be a good representation of UK institutional investors.

Secondly, there are very few empirical studies on institutional herding behaviour in the UK markets. To the best of the author's knowledge, there are only four works so far studying investor herd behaviour in the UK. Hwang & Salmon (2004, 2007) and Khan & Hassairi (2011) examine the UK stock market and find significant and persistent market-wide equity return herding. However the investors examined in these studies are not distinguished into different groups, which means that the herding tested in a market-wide level is the mixture of both institutional and individual investors' behaviour. Wylie (2005) analyses the proportion of net buying or selling in one stock by UK equity mutual fund managers to find evidence of investors herding in individual stocks.

Thirdly, until now the institutional investors' herd behaviour has been largely examined at the stock level, i.e. investors following each other to buy or sell the same stock or group of stocks. It has not been studied at a portfolio level, where institutional investors mimic a benchmark investment portfolio or market portfolio rather than forming a portfolio according to their own information.

The hypothesis that will be tested in this study is that institutional investors, represented by fund managers, herd on market return, i.e. market return is used as a benchmark when institutional investors construct the investor portfolio. This is an investment style herding.

The daily price of the open-ended funds, NAVs of closed-end funds and FTSE 350 Index are collected to calculate the fund and the market returns. Other financial and economic data such as the FTSE 350 Volume, S&P 500 Index, UK 3-month Treasury Bill rate, and UK 10-year Government bond rate have been collected and used in the study as sample variables for other economic factors.

In the UK, Unit Trusts are quoted at bid and ask prices for buying and selling respectively, and the prices used for calculating the returns in this research are daily middle prices of bid and ask. OEIC prices are the unified quoted prices without being

[33] Source from: Share Ownership: Ownership of UK quoted shares 2010, www.statistics.gov.uk

adjusted for fees and charges. By the different ways they pay out their dividends and other investment incomes, investment funds of Unit Trust and OEICs are often classified as income unit (or share) or accumulation unit (or share). Income Units pay out dividends and other income as cash directly to investors, normally shortly after the fund distribution date, whereas Accumulation Units do not pay the cash out, and instead, they reinvest them directly into the fund, which inflates the funds' capitalisation. The price of each unit increases with the number of units remaining the same. In order to keep the prices of different classes of fund comparable, the prices of Income Units used in the following study are adjusted for dividend and other investment incomes that have been paid out by cash. Some of the mutual funds hold both Accumulation Unit and Income Unit accounts. In order to avoid duplication, only the Income Unit account is chosen in the sample if the fund has both accounts.

Daily data are used as the basis to calculate weekly and monthly variables. Daily returns are calculated by applying $R_t = lnP_t - lnP_{t-1}$. Weekly returns are calculated as: $R_t = lnP_t - lnP_{t-5}$, and monthly returns are calculated using the prices at the last trading day of each month: $R_{t_m} = lnP_{t_m} - lnP_{t_m-1}$. To eliminate calendar effects, daily returns are analysed using market time regressions, i.e. excluding non-trading days such as weekends and public holidays, and weekly returns are the weekly Wednesday returns. The weekly and monthly data used in the study are non-over lapping data.

The sample period is from 01 January 1996 to 30 June 2010. It covers the major financial incidents of the 1997 Asian crisis, the 1998 Russian crisis, the dotcom bubble and its crash, and the recent financial crisis.

A summary of daily, weekly and monthly variables is presented in Table 5.1A, B and C respectively. It should be noted that since over-lapping data are not used, the number of observations significantly decreases from daily data to monthly data. This may lead to sample size problems in the later estimations, and will be discussed in a later section (section 5.4).

Looking at the values of kurtosis of variablesof R_m , volume and R_m^F , it suggests that the distributions for the series have fatter tails than a normal distribution. The excess kurtosis generally decreases from daily frequencies to monthly frequencies among these variables. This feature stands out more in the volume distribution, since the Jarque-Bera test cannot reject the null of normal distribution in the monthly frequencies. The Augmented Dickey-Fuller (ADF) tests show that the volume cannot reject hypothesis of unit root and the ADF tests are rejected for the first difference of volume in all three frequencies. Thus the first difference of the volume is used in the analysis.

In the daily data, the maximum market return is about 9% on 24/11/2008. It is accompanied by the greatest volatility, CSSD and CSAD for both open-ended funds and closed-end funds. The maximum foreign market return appears on 13/10/2008, and the largest trading day in the sample period is 19/09/2008. The minimum value of daily market return is -8.83% on 10/10/2008 and the foreign market return is -9.47 on 15/10/2008. These may suggest that the large return turbulence is the impact of the financial market crisis, especially the 2007-8 Global Financial Crisis.

In the weekly data, the maximum return is in the third week of March 2003 (beginning 17/03/2003) accompanied by the greatest volatility. The minimum market weekly return is in the first week of October 2008, and at the same time the foreign market return reaches its minimum. This may imply the co-movement of global markets on certain factors. The date with largest CSAD and CSSD for mutual funds is the last week of October 2008. The largest trading week is the second week of August 2007. The weekly data again gives some hints for the impact of the financial crisis on the variables and the influence foreign markets would have on the UK market.

The monthly data exhibits similar characteristics to the daily and weekly data. The extreme values are more likely to appear during financial crisis periods. The maximum value of the market return is in April 2009 and the minimum value in September 2008. Both the absolute return and volatility are at their maximum in October 2008. The largest volume of shares has been traded in March 2006 and the biggest monthly increase of trade volume happened in February 2000.

Table 5.1A: Statistics of Daily Basic Data for investigating mature funds

Table 5.1A provides summary statistics of the basic data series. The data are daily and cover the period 1st January 1996 to 30th June 2011 (3911 observations).

Variable definitions:

$\boldsymbol{R_m}$: is the market return which is calculated from FTSE 350 Price Index; $|\boldsymbol{R_m}|$ is the absolute value of market return; $\boldsymbol{R_m^2}$ is the square of market return. **CVOL**: the change of market trading volume calculated in the same manner as market return (i.e. $100 * \ln\left(\frac{volum_t}{volume_{t-1}}\right)$); **Volume**: the actual market trading volume; R_m^F : the foreign market return which is calculated by use S&P 500 Price Index.**$\mathbf{CSAD_{op}}$**: Cross Section Absolute Deviation of open-ended funds; **$\mathbf{CSSD_{op}}$**: Cross Section Standard Deviation of open-ended funds; **$\mathbf{SD_{op}}$** the standard deviation of the time very betas of the 84 open-ended funds. **$\mathbf{LogSD_{op}}$** is nature log of beta standard deviation;**$\mathbf{CSAD_{cl}}$**: Cross Section Absolute Deviation of closed-end funds; **$\mathbf{CSSD_{cl}}$**: Cross Section Standard Deviation of closed-end funds; **$\mathbf{SD_{cl}}$** the standard deviation of the time very betas of the 119 closed-end funds. **$\mathbf{LogSD_{cl}}$** is nature log of beta standard deviation.

AC (1) is autocorrelation coefficient at one lag. **ADF** is Augmented Dickey-Fuller test statistic with maximum 250 lags.
***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

Variable	Mean	Std. Dev.	Min	Min Date	Max	Max Date	Skewness	Kurtosis	Jarque-Bera	AC(1)	ADF
R_m	0.013904	1.189161	-8.82747	10/10/2008	9.005264	24/11/2008	-0.18145	8.979935	5848.79***	-0.022	-29.9221***
$\|R_m\|$	0.83052	0.851091	0		9.005264	24/11/2008	2.974709	16.66257	35509.85***	0.245	-9.0692***
R^2_m	1.413935	3.99217	0		81.09479	24/11/2008	9.966363	148.2781	3504098***	0.221	-5.8113***
CVOL	0.041898	33.52859	-594.353	19/02/1998	571.6285	20/02/1998	-0.32059	79.42532	951878.8***	-0.373	-23.2423***
Volume	1574245	788967.9	1666	19/02/1998	5489280	19/09/2008	0.374044	2.803227	97.50675***	0.855	-3.6455***
R^F_m	0.019304	1.287385	-9.46952	15/10/2008	10.9572	13/10/2008	-0.17047	10.57503	9369.672***	-0.063	-48.6596***
$CSAD_{op}$	0.767267	0.654945	0.117148	15/10/2010	8.178290	24/11/2008	3.315474	21.77003	64577.71***	0.518	-7.7110***
$CSSD_{op}$	0.902114	0.676788	0.167339	25/08/2006	8.31677	24/11/2008	3.237223	21.10783	60263.93***	0.560	-7.4650***
$CSAD_{cl}$	0.7030	0.4419	0.1749	03/04/1996	5.6428	24/11/2008	3.0227	19.7802	51853.71***	0.496	-7.8282***
$CSSD_{cl}$	0.9601	0.5699	0.2500	03/04/1996	7.9842	31/12/2008	3.1213	22.6864	69523.42***	0.501	-7.9835***

Table 5.1B: Statistics of Weekly Basic Data for investigating open-ended funds

Table 5.1B provides summary statistics of the basic data series. The data are weekly and cover the period 1st January 1996 to 30th June 2011.

Variable definitions:

$\boldsymbol{R_m}$: is the market return which is calculated from FTSE 350 Price Index; $|\boldsymbol{R_m}|$ is the absolute value of market return; $\boldsymbol{R_m^2}$ is the square of market return. **CVOL**: the change of market trading volume calculated in the same manner as market return (i.e. $100 * \ln\left(\frac{volum_t}{volume_{t-1}}\right)$); **Volume**: the actual market trading volume; R_m^F : the foreign market return which is calculated by use S&P 500 Price Index. **CSAD$_{op}$**: Cross Section Absolute Deviation of open-ended funds; **CSSD$_{op}$**: Cross Section Standard Deviation of open-ended funds; **SD$_{op}$** the standard deviation of the time very betas of the 84 open-ended funds. **LogSD$_{op}$** is nature log of beta standard deviation;**CSAD$_{cl}$**: Cross Section Absolute Deviation of closed-end funds; **CSSD$_{cl}$**: Cross Section Standard Deviation of closed-end funds; **SD$_{cl}$** the standard deviation of the time very betas of the 119 closed-end funds. **LogSD$_{cl}$** is nature log of beta standard deviation. **TS**: the Term Spread defined as the difference between the rate on UK 10 year gilt and UK 3 month Treasury bill. **RTB**, the relative treasury bill rate, is defined as the difference between the UK 3 month treasury bill rate and its 12-month moving average. **AC (1)** is autocorrelation coefficient at one lag. **ADF** is Augmented Dickey-Fuller test statistic with maximum 52 lags. **Obs** is number of observation.

***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

Variable	Obs	Mean	Std. Dev.	Min	Min Date	Max	Max Date	Skewness	Kurtosis	Jarque-Bera	AC(1)	ADF
R_m	807	0.062962	2.397154	-12.3902	08/10/2008	12.73801	13/03/2003	-0.40106	6.109077	346.6655***	-0.075	-30.5761***
$\|R_m\|$	807	1.753296	1.634764	0.007702	02/08/2000	12.73801	19/03/2003	2.168343	10.52443	2536.128***	0.309	-6.1118***
$R^2{}_m$	807	5.74319	12.93042	5.90E-05	02/08/2000	162.2569	19/03/2003	6.533577	62.73042	125706.2***	0.316	-10.1615***
CVOL	807	0.191809	33.77084	-203.63	30/12/1998	201.4175	06/01/1999	-0.27843	12.87063	3286.487***	-0.231	-5.4156***
Volume	807	7619363	3700434	369475	30/12/1998	1.62E+07	15/08/2007	0.077392	1.924897	39.67094***	0.868	-1.5943
$R^F{}_m$	807	0.090252	2.495023	-16.4508	08/10/2008	10.1824	16/10/2002	-0.55372	6.81817	531.4373***	-0.053	-29.9482***
CSAD$_{op}$	807	0.896307	0.579898	0.228504	31/12/2003	5.418843	29/10/2008	2.397622	11.69984	3318.170***	0.488	-8.3242***
CSSD$_{op}$	807	1.119692	0.645256	0.314122	23/05/2007	6.293215	29/10/2008	2.308118	11.58805	3196.536***	0.519	-7.8868***
SD$_{op}$	808	0.397732	0173175					2.238993	12.54376	3741.571***	0.146	-24.4614***
LogSD$_{op}$	808	-0.999394	0.385855					0.251224	3.634850	22.06809***	0.209	-15.0690***
TS	807	0.209439	3.571555					2.476009	20.18018	10749.27***	-0.062	-5.7602***
RTB	808	-0.002795	2.931903					-1.554069	34.59553	33933.90***	-0.115	-11.72175***
CSAD$_{cl}$	808	1.4220	0.7477	0.3946	29/06/2005	7.5788	29/10/2008	2.5860	15.3109	6002.99***	0.506	-5.7849***
CSSD$_{cl}$	808	1.9782	0.9911	0.5792	29/06/2005	9.2490	29/10/2008	2.3195	12.5475	3793.38***	0.527	-4.0091***
SD$_{cl}$	808	0.5815	0.2485					2.3625	11.2199	3026.38***	0.104	-25.550***
LogSD$_{cl}$	808	-0.6101	0.3486					0.9385	3.9285	147.6457***	0.159	-13.316***

Table 5.1C: Statistics of monthly Basic Data for investigating open-ended funds

Table 5.1C provides summary statistics of the basic data series. The data are monthly and cover the period 1st January 1996 to 30th June 2011.

Variable definitions:

R_m : is the market return which is calculated from FTSE 350 Price Index; **CSAD**: Cross Section Absolute Deviation; **CSSD**: Cross Section Standard Deviation; $|R_m|$ is the absolute value of market return; R_m^2 is the square of market return. **CVOL**: the change of market trading volume calculated in the same manner as market return (i.e. $100 * \ln(\frac{volum_t}{volume_{t-1}})$; **Volume**: the actual market trading volume; R_m^F : the foreign market return which is calculated by use S&P 500 Price Index. **CSAD$_{op}$**: Cross Section Absolute Deviation of open-ended funds; **CSSD$_{op}$**: Cross Section Standard Deviation of open-ended funds; **SD$_{op}$** the standard deviation of the time very betas of the 84 open-ended funds and the betas are estimated by applying OLS method on daily fund returns, according to Hwang &Salmon(2004) approach. **LogSD$_{op}$** is nature log of beta standard deviation; **CSAD$_{cl}$**: Cross Section Absolute Deviation of closed-end funds; **CSSD$_{cl}$**: Cross Section Standard Deviation of closed-end funds; **SD$_{cl}$** the standard deviation of the time very betas of the 119 closed-end funds. **LogSD$_{cl}$** is nature log of beta standard deviation. **TS**: the Term Spread defined as the difference between the rate on UK 10 year gilt and UK 3 month Treasury bill. **RTB**, the relative treasury bill rate, is defined as the difference between the UK 3 month treasury bill rate and its 12-month moving average. A**C (1**) is autocorrelation coefficient at one lag. **ADF** is Augmented Dickey-Fuller test statistic with maximum 12 lags. **Obs** is number of observation.

***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

Variable	Obs	Mean	Std. Dev.	Min	Min Date	Max	Max Date	Skewness	Kurtosis	Jarque-Bera	AC(1)	ADF
R_m	186	0.292689	4.248502	-14.3488	30/09/2008	8.762429	30/04/2009	-0.8473	3.957803	29.36529***	0.068	-12.6421***
$\|R_m\|$	186	3.272909	2.714049	0.000498	30/06/2003	14.34876	30/09/2008	1.364873	5.018998	89.34097***	0.143	-5.3838***
$R^2{}_m$	186	18.03839	29.81232	2.48E-07	30/06/2003	205.8868	30/09/2008	3.238832	15.98463	1631.846***	0.207	-10.9572***
CVOL	186	0.560873	21.0768	-49.1089	29/08/2008	60.58278	29/02/2000	0.135812	3.049526	0.5908	-0.456	-4.2846***
Volume	186	3.31E+07	1.50E+07	8445925	30/08/1996	6.18E+07	31/03/2006	-0.04056	10812754	10.97502***	0.861	-1.5966
$R^F{}_m$	186	0.410092	4.724222	-18.5637	31/10/2008	9.232381	31/03/2000	-0.91078	4.598617	44.0619***	0.112	-12.086***
CSAD$_{op}$	186	1.315180	0.618664	0.494403	31/07/2008	3.768470	30/07/1999	1.377736	5.006491	90.04444***	0.413	-8.6963***
CSSD$_{op}$	186	1.737894	0.826543	0.670414	31/07/2008	5.011428	30/09/2009	1.472912	5.406958	112.1528***	0.439	-4.2822***
SD$_{op}$	186	0.256028	0.067260					1.662443	9.651039	428.5067***	0.214	-10.8633***
LogSD$_{op}$	186	-1.393236	0.245789					0.212696	4.201390	12.58829*	0.265	-10.2879***
TS	185	0.908548	7.886121					3.341009	21.04021	2852.844***	0.439	-4.373438***
RTB	186	0.011128	8.000211					-3.326831	38.59983	10165.05***	0.614	-6.609223***
CSAD$_{cl}$	186	2.8803	1.2518	1.2417	31/08/2004	8.0128	31/10/2008	1.3777	5.0065	90.044***	0.458	-4.7876***
CSSD$_{cl}$	186	4.0611	1.8201	1.6946	31/08/2006	11.8327	29/02/2000	1.4729	5.4070	112.153***	0.473	-4.7064***
SD$_{cl}$	186	0.3694	0.0635					1.8751	8.1598	315.326***	0.215	-10.879***
LogSD$_{cl}$	186	-1.0085	0.15542					1.1542	5.1402	76.8009***	0.234	-10.659***

Calendar effects on asset return have been well documented. The most pervasive are the day-of-the-week effect and the January Effect, which state that the distribution of stock returns varies according to the day of the week and month of the year. Cross (1973) and French (1980) investigate the weekend effect and find evidence that the average return on Monday is significantly less than that of the other days of the week. Calendar effects are not limited to the equity markets, they have also been found present in other financial markets such as the futures market and bond market (Cornell 1985; Dyl and Meberly, 1988). Therefore, statistic tests have been conducted according to French's (1980) method for the day-of-the-week and January effect.

The following regression is used to formally test the effects:

$$R_t = \alpha + \sum_{n=2}^{N} \delta_n D_{nt} + \varepsilon_t \qquad (5.1)$$

where $N = 2,3,4,5$ represent Tuesday to Friday respectively for the day-of-the-week effect, and $N = 2, \dots, 12$ represent February to December respectively for the month-of-the-year effect; R_t is the return and the dummy variables indicate the day (month) of the week (year) on which the return is observed, for example $D_{2t} = Tuesday$, $D_{3t} = Wednesday$, etc.

Table 5.2 Panel A presents the result for the testing of day-of-the-week. The coefficients for market return, CSAD, CSSD, and foreign market return (represented as return of S&P index) are not statistically significant suggesting that there is no different between Monday and the days in the rest of the week, i.e. no day-of-the-week effect among these variables. This is different to the results of Cross (1973) and French (1980), however, the coefficients of volatility (calculated as the square of the market return) show that the volatility on Monday is statistically significantly larger than the rest of the days of the week. The coefficients of CVOL and volume suggest the trading volumes on Monday are statistically less than those of rest days of the week. Panel B of Table 5.2 presents the result for testing month-of-the-year. The significant coefficients of volume show that January is the greatest trading month over a year. However, the insignificant coefficients of all other variables suggest that there is no seasonal effect among these variables.

Table 5.2: Test results of the 'Day-of-the-week' and 'Month-of-the-year' effects

Table 5.2 reports the results of regressions of the following general form: $V_t = \alpha + \sum_{n=2}^{N} \delta_n D_{nt} + \varepsilon_t$,
where N = 2,3,4,5 represent Tuesday to Friday respectively for the day-of-the-week effect, and N = 2, … ,12 represent February to December respectively for the month-of-the-year effect; V_t is the variable Return, Volatility, CSAD, CSSD, CVOL, Volume and R_m^F; the dummy variables indicate the day (month) of the week (year) on which the return is observed, for example D_{2t} = Tuesday, D_{3t} = Wednesday, etc.

Variable definitions:

$\boldsymbol{R_m}$: is the market return which is calculated from FTSE 350 Price Index; **CSAD$_{op}$**: Cross Section Absolute Deviation of open-ended fund; **CSSD$_{op}$**: Cross Section Standard Deviation of open-ended funds; $|\boldsymbol{R_m}|$ is the absolute value of market return; $\boldsymbol{R_m^2}$ is the square of market return. **CVOL**: the change of market trading volume calculated in the same manner as market return (i.e. $100 * \ln\left(\frac{volum_t}{volume_{t-1}}\right)$); **Volume**: the actual market trading volume; R_m^F : the foreign market return which is calculated by use S&P 500 Price Index; **CSAD$_{cl}$**: Cross Section Absolute Deviation of closed-end fund; **CSSD$_{cl}$**: Cross Section Standard Deviation of closed-end funds;
***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

Panel A: Day-of-the-week effect									
Variable	**Return**	**Volatility**	**CSAD$_{op}$**	**CSSD$_{op}$**	**CVOL**	**Volume**	**$R^F{}_m$**	**CSAD$_{cl}$**	**CSSD$_{cl}$**
Monday	0.042791	1.820102***	0.783868***	0.918625***	-19.39573***	1316881***	0.040554	0.733287***	0.997966***
Tuesday	-0.02206	-0.497769**	0.006392	0.007660	38.9829***	281715.5***	-0.00168	-0.029029	-0.039430
Wednesday	-0.0911	-0.529973***	-0.039710	-0.036629	23.59725***	340611.7***	-0.02403	-0.040037*	-0.041429
Thursday	-0.04082	-0.475486**	-0.035190	-0.033946	19.40647***	359993.2***	-0.03119	-0.043987*	-0.067799**
Friday	0.013195	-0.493991**	-0.012834	-0.018107	13.43067***	282550.1***	-0.04801	-0.035680	-0.037655
Panel B: Month-of-the-year effect									
January	-1.52998	23.3276***	1.384623***	1.862988***	31.61079***	34600000***	-0.35696	3.321335***	4.608098***
February	2.206546	-12.1339	0.001292	-0.08776	-34.76399***	-1113364	-0.83185	-0.754212*	-0.956079
March	2.285215	-12.9988	-0.08931	-0.15303	-21.91889***	2155162	1.848947	-0.579651	-0.602582
April	3.855679	-5.0827	-0.21122	-0.2565	-49.08971***	-4216950	2.668611	-0.693547	-0.940126
May	1.007517	-12.7157	-0.13207	-0.18685	-26.04125***	-1764655	0.757159	-0.550491	-0.758654
June	-0.0769648*	-10.29	-0.22589	-0.26512	-29.53559***	-1503398	-0.22338	-0.490003	-0.481036
July	1.990038	-3.55065	-0.03902	-0.11552	-27.87352***	370614.5	0.302156	-0.471059	-0.651841
August	1.923802	-7.48075	-0.13481	-0.256	-48.99729***	-5263856	-0.76156	-0.581635	-0.665610
September	-0.0058431***	21.12739	0.080293	0.052361	-14.74868***	444146.1	0.13581	-0.134483	-0.217296
October	2.434498	3.342441	0.154089	0.154101	-27.06851***	1795341	1.359284	-0.031199	-0.125978
November	2.367191	-12.7434	0.145379	0.163143	-36.3505***	1371.054	2.102456	-0.412974	-0.620548
December	3.994865	-9.51204	-0.36602	-0.5367*	-57.87442***	-8659587	1.872575	-0.565576	-0.513989

CH suggested that the use of different frequency of data would reveal the different time horizons of herd behaviour affecting market prices. If the use of daily data implies that herd behaviour is a very short-lived phenomenon, the use of monthly data then indicates that herd behaviour requires a longer time to affect asset prices. By the nature of decision making processes of institutional investors, it is more likely that their herding behaviour would take a longer time to have an impact on market prices. Investor sentiment, however, may also cause herding behaviour which could be in a relatively short-term. The possible of short-term herding effect is also of interest. Therefore, daily, weekly and monthly data are used for analysing herding behaviour of institutional investors in representing short, medium and long time horizons.

5.3 Portfolio herding in market stress periods

CH propose that herd behaviour is more likely to exist during market extreme periods. The 'extreme' market movements are defined as the lower and upper tail of the market returns distribution at 5 percent (or 1 percent). Following such criterion, equation (4.1) has been estimated by restricting D_t^L and D_t^U to 5% and then1% of the lower and upper tails. The rationale of this analysis is that if fund managers form their portfolio in a style of imitating the return of market average, the return dispersion should be less in the turbulent time than that of normal time. Therefore, the coefficients of the two dummy variables are expected to be negative. The regression results are very similar in CSAD (Table 5.3A) and CSSD (Table 5.3B) measures.

In fact, the estimated coefficients display a very similar picture in both open-ended funds and closed-end funds. The positive significant of coefficients, β_1 and β_2, demonstrate that return dispersions are greater during extreme market periods versus normal periods. This indicates the absence of herding in market stress time. This finding is consistent with previous works, such as CH's test on US stock market data, Demirer & Kutan's (2006) test on the Chinese stock market, Lin & Swanson (2003) and Demirer et al's. (2010) test on the Taiwanese stock market, Gleason et al. (2003) study on commodity futures traded on European exchanges, and Gleason et al. (2004) on Exchange Trade Funds.

When examining the asymmetric dispersion in the extreme up- and down-market, the application of daily data suggests that dispersions of both open-ended funds and closed-end funds are at a greater level during extreme up-market than that of extreme down-market. This is in line with Christie and Huang (1995), Gleason, Mathur and Peterson (2004), Caporale, Economou, & Philippas (2008) and Tan, Chiang, Mason & Nelling (2008).

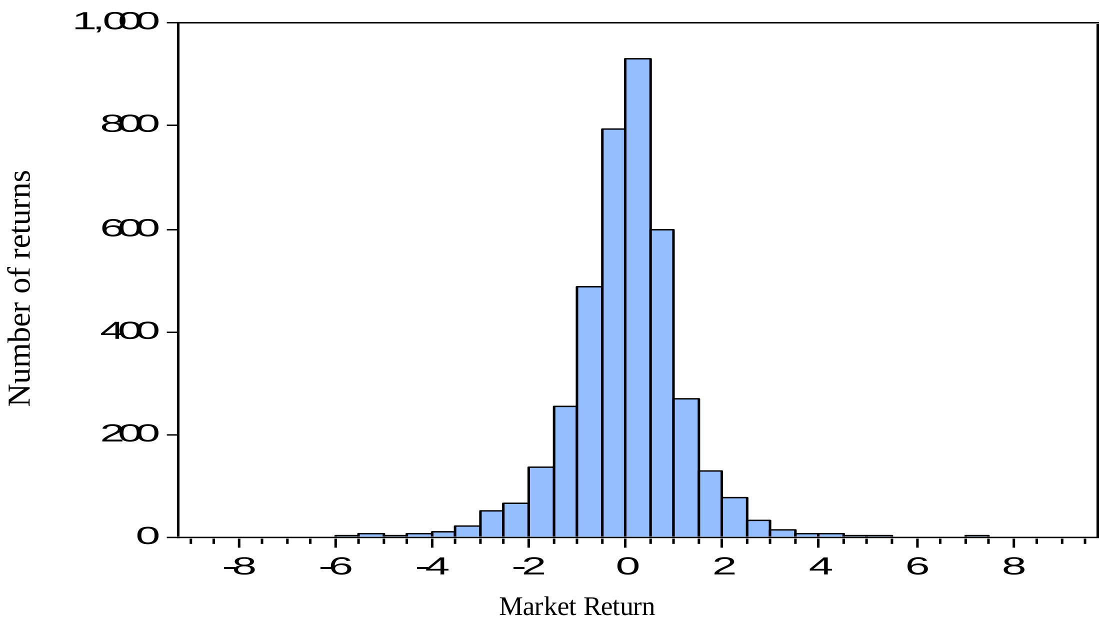
The asymmetric return dispersion in extreme up- and down-market may be caused by investors' asymmetric attitude to losses. According to Prospect theory, an economic agent's response to loss is more extreme than to that of gain (Tversky and Kahneman, 1986). When market return is in the extreme lower tail, the heavy losses of the overall market promote pessimistic expectations among investors. The fear that their investment portfolio performs worse than the market average leads fund managers to match up their investment portfolios to the market portfolio. These matching and catching up processes can protect fund managers' reputation by blaming the losses to the overall market performance rather than their stock picking skill. When market return is in the extreme upper tail, opportunism expectation arises among investors. Performance of fund investment portfolio is expected to 'beat the market', hence fund managers can be rewarded for out-performance. This leads the manager to structure their portfolio to maximise the expected portfolio returns according to their private information rather than just following the overall market consensus. The asymmetric effect may be a sign of investor sentiment impact on fund managers forming investment portfolio. However, it does not necessarily suggest herding behaviour since the return dispersion in the extreme markets is greater than that in the normal time.

The CH method mainly looks for herding evidence by examining the return dispersions during the extreme period (up and down 5% or 1% distribution tail) against that of the normal periods. If the average dispersions in both of the tails are greater than that in the normal time, no herding is proved. If the dispersion in either of the tails is less than that of the normal period, there is evidence of herding. One key point of CH approach is the criteria that are applied for defining the market extreme. CCK and HS argue that since the criteria of judging market extreme level plays an important role in CH method, the statistical result is significantly subject to the criteria used to define the market stress and how many samples fall into the interval.

From Figure 5.1, it can be seen that the market returns have a high peak and fat tail distribution, which is confirmed by the parameters of Kurtosis and the significance of J-

B test. However, the distribution chart also shows that the returns are highly concentrated in the significant interval. The number of outliers is a tiny fraction of the total observation. For example, the number of samples in the daily returns that lie in the 5% upper tail is 88 and in the 5% lower tail is 126 as compared to the total sample size of 3911. In the 1% criteria, the number of returns distributed in the upper and lower tails is 38 and 53 respectively. The monthly data is an extreme case as there are no returns in the 1% up tail. HS also point out that market stress does not necessarily imply the market as a whole should display either large negative or large positive returns. For example, large price swings in FTSE100 Index have been seen in some periods while the UK stock market as a whole has not shown any dramatic change in the aggregate. In addition, the method to use 1% or 5% distribution as the cut-off point to identify the extreme market is rather arbitrary. Practically, what constitutes an extreme return can vary among different investors and is variable over different periods. Moreover, the CH method is more likely to capture herding only during market stress periods. It should be noted, however, that herding may occur to some extent over the entire return distribution and may become more pronounced during the market extreme periods.

Figure 5.1: Distribution density function of daily market return



As stated in section 3.6, during the sample period, the market has experienced several major financial crises. They are the 1997 Asian financial crisis, the 1998 Russian financial crisis, the dotcom bubble & crash and the 2007-8 global financial crisis. These events show either large negative or positive returns, or serve as a turning point of the general market trend, i.e. a reverse from a bull market to a bear market and they all have a significant impact on the local and global economies. The pattern of market prices in each crisis appears to display similar characteristics: a quick rise in market prices in a continuous process before the crisis starts, which normally displays a feature of low return volatility in a continuous period, followed by a sharp fall or falls of prices, which are accompanied by great return volatility. These phenomena are sometimes described as the process of bubble building and bursting in the financial literature.

One argument states that an asset bubble is caused by investor irrational investment activities and the bursting of the bubble is actually a process of correcting asset prices to reverse back to their fundamental. The argument suggests that during a bubble building period, the investment decisions are not made based on asset fundamental value but on psychological biases involved in the decision making process, and herd instinct is believed to be present in such decision-making processes to reduce investors' uncertainty. When the market is overvalued by some irrational agents through their trading activities, sophisticated (i.e. institutional investors) may ride the bubble to maximise their profits (Abreu & Brunnermeier, 2003), or initiate a trade with the expectation of the positive-feedback traders buying those securities at a higher price later and drive stock prices to deviate more from their fundamentals (DeLong et al., 1990). Accordingly, two hypotheses will be examined in this study:

Hypothesis 1: if the continuously rising asset price in the bubble building period is a result of the investors herd behaviour, the herding parameters are expected to be statistically significant.

Hypothesis 2: if the crisis itself is a process of asset prices reverting to the fundamental rather than herding behaviour of investors, the herding parameters are expected to be statistically not significant.

In order to capture herd behaviour in the unrest periods of the market, an alternative criterion is utilised for investigating the severe market events. Using the non-crisis, pre-crisis and in-crisis periods defined in section 3.6, CH method is used for the empirical examination of whether the return dispersion is significantly lower than average during the market stress period, which is classified as the pre-crisis period and the in-crisis period now.

$$S_t = \alpha + \beta_1 D_t^{Pre} + \beta_2 D_t^{in} + \epsilon_t \tag{5.2}$$

Where S_t represents the herding measures of CSAD or CSSD. $D_t^{pre} = 1$if day t is in the pre-crisis period; otherwise it is equal to zero. $D_t^{in} = 1$ if day t is in the in-crisis period; otherwise it is equal to zero. The estimation results are presented in Table 5.4

The results of both open-ended funds and closed-end funds present very similar pictures. In the daily frequency, the significant negative values of β_1 indicate that the return dispersions in the pre-crisis periods are lower than that in the non-crisis period. This suggests investor herd behaviour does exist in the pre-crisis in the daily data. The positive and significantβ_2 implies that there is no evidence of herd behaviour in the crisis period. These regression results generally support the argument that herd behaviour exists in the bubble building time, i.e. the pre-financial crisis period, and the financial crisis is a process of market reversal back to the fundamental. These results support hypothesis 1 and hypothesis 2. However, when the regressions use weekly and monthly data, the significant levels of β_1 indicate that return dispersions during pre-crisis periods have hardly any difference from those in the normal time, providing no evidence of herding behaviour in pre-crisis period. $\beta_2$is still positive and significant, confirming the non-herding suggestion in financial crisis periods.

Comparing the coefficients in different frequencies, the significant level of return dispersion in pre-crisis is less than that during the normal period, falling significantly from daily data to monthly data. This may suggest that herd behaviour is greatest in the daily investment activities, and then decreases alongside the increases of investment interval. This again supports the idea that herd behaviour is greater in the short term investment interval as compared to the long term interval. Moreover, the CSAD measures show slightly stronger statistical signs of herding evidence, which indicates the CSAD is more likely to be the better measure of herding as suggested by CCK.

The linear CH model provides a simple method to detect herd behaviour under specific market conditions, for example market stress time or financial crisis period. The approach relies on assuming that there is no herding in the normal period, therefore the return dispersions in this period become a benchmark for others to be compared to. A lower level than the benchmark return dispersion becomes evidence of herd behaviour. The limitation of this approach is that it needs a benchmark return dispersion to compare with. Investors are assumed to make investment decisions according to asset fundamentals during the benchmark period. In practice, however, to identify the benchmark itself can be an issue needed to be studied further. CCK, therefore, suggest that examining the relationship between return dispersion and the market return can be a more powerful method to test market herd behaviour.

Table 5.3A: Regression Coefficients: Dispersions mutual funds during periods of market stress measuring by CSAD

Table 5.3A reports the results of regressions of the following general form: $S_t = \alpha + \beta_1 D_t^U + \beta_2 D_t^L + \epsilon_t$,
Where $S = CSAD\ or\ CSSD$; if the market return on day t lies in the extreme lower tail of the distribution, $D_t^L = 1$; otherwise it is equal to zero. If the market return on day t lies in the extreme upper tail of the distribution, $D_t^U = 1$; otherwise it is equal to zero. The sample period is January 1996 – June 2010, t-statistics are given in parentheses. The F_c statistics test the null hypotheses that $\beta_1 = \beta_2$.
The regressions are estimated by Least Squares with Newey-West HAC standard Errors and Covariance.

Variable definitions:

CSAD: Cross Section Absolute Deviation; ***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

CSAD	Market return in the extreme upper/lower 5% of the return distribution						Market return in the extreme upper/lower 1% of the return distribution					
	Open-ended funds			**Closed-end funds**			**Open-ended funds**			**Closed-end funds**		
	Daily	Weekly	Monthly	Daily	Weekly	Monthly	Daily	Weekly	Monthly	Daily	Weekly	Monthly
α	0.6976*** (44.1155)	0.8411*** (29.1270)	1.2616*** (20.9130)	0.6398*** (62.8214)	1.3381*** (33.5787)	2.7466*** (20.8053)	0.7273*** (41.6586)	0.8644*** (28.5829)	1.7075*** (19.3959)	0.6662*** (57.9730)	1.3734*** (33.0261)	2.8224*** (19.5381)
β_1	1.5234*** (9.2936)	1.0164*** (5.3625)	1.3796*** (22.8687)	1.3429*** 13.4936)	2.0853*** (5.0588)	1.9667*** (14.8971)	2.1349*** (8.2720)	1.7365*** (5.1073)	N/A	1.8746*** (11.6025)	3.8574*** (5.7276)	N/A
β_2	1.0982*** (12.0283)	1.0099*** (6.2341)	0.8577*** (2.6461)	1.0287*** (15.2082)	1.2427*** (7.7576)	2.2887*** (3.6591)	1.4626*** (8.4998)	1.4483*** (7.1074)	1.4154*** (3.1036)	1.4189*** (13.3391	1.8335*** (6.8947)	2.6919*** (4,3170)
Adj-R^2	0.200647	0.155094	0.113675	0.3615	0.2265	0.1737	0.163979	0.139932	0.056945	0.3026	0.2226	0.0929
S.D.	0.585564	0.533035	0.582440	0.3531	0.6576	1.1379	0.598844	0.537796	0.802665	0.3691	0.6593	1.1922
SSR	1339.994	228.4373	62.08031	487.3508	348.1120	236.9470	1401.462	232.5367	118.5457	532.3050	349.8813	261.5142
Log LH	-3454.877	-635.8414	-161.8720	-1477.0140	-806.3191	-286.4369	-3542.584	-643.0181	-222.0309	-1649.5530	-808.3673	-295.6116
F_c	5.789369**	0.000726	2.702739	11.3849***	3.9652**	0.2456	4.409856**	0.534973	N/A	7.0287***	6.7780***	-

Table 5.3B: Regression Coefficients: Dispersions of mutual funds during periods of market stress measuring by CSSD

Table 5.3B reports the results of regressions of the following general form: $S_t = \alpha + \beta_1 D_t^U + \beta_2 D_t^L + \epsilon_t$,
Where $S = CSAD\ or\ CSSD$; if the market return on day t lies in the extreme lower tail of the distribution, $D_t^L = 1$; otherwise it is equal to zero. If the market return on day t lies in the extreme upper tail of the distribution, $D_t^U = 1$; otherwise it is equal to zero. The sample period is January 1996 – June 2010, t-statistics are given in parentheses.
The F_c statistics test the null hypotheses that $\beta_1 = \beta_2$.
The regressions are estimated by Least Squares with Newey-West HAC standard Errors and Covariance.

Variable definitions:

CSSD: Cross Section Standard Deviation ***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

CSSD	Market return in the extreme upper/lower 5% of the return distribution						Market return in the extreme upper/lower 1% of the return distribution					
	Open-ended funds			**Closed-end funds**			**Open-ended funds**			**Closed-end funds**		
	Daily	Weekly	Monthly	Daily	Weekly	Monthly	Daily	Weekly	Monthly	Daily	Weekly	Monthly
α	0.8259*** (49.1291)	1.0547*** (31.3515)	1.6668*** (19.6745)	0.8855*** (63.0678)	1.8798*** (32.9287)	3.8884*** (19.4182)	0.8585*** (46.0283)	1.0819*** (30.8731)	1.7075*** (17.9956)	0.9168*** (59.1658)	1.9210*** (32.9221)	3.9752*** (18.6961)
β_1	1.6625*** (9.9411)	1.3298*** (5.7053)	1.8978*** (22.4019)	1.5641*** (12.4289)	2.3423*** (5.0263)	2.2755*** (2.2755)	2.3228*** (9.1132)	2.4689*** (7.2997)	N/A	2.1995*** (10.5166)	4.4734*** (6.0088)	N/A
β_2	1.2043*** (13.1670)	1.1284*** (6.7117)	1.1327** (2.5456)	1.2239*** (14.7229)	1.5061*** (7.0557)	2.9851*** (3.4820)	1.6003*** (9.5533)	1.5857*** (7.2629)	1.4154*** (3.2771)	1.6665*** (12.6167)	2.1805*** (5.9498)	3.9927*** (4.5422)
Adj-R^2	0.2248	0.1754	0.1130	0.3006	0.1737	0.1355	0.1827	0.1646	0.0569	0.2507	0.1736	0.0969
S.D.	0.5959	0.5859	0.7785	0.4766	0.9009	1.6923	0.6119	0.5898	0.8027	0.4934	0.9010	1.7296
SSR	1387.6770	276.0341	110.8961	887.7886	653.3392	524.0922	1463.0350	279.6653	118.5457	951.2073	653.4350	550.4342
Log LH	-3523.2540	-712.2089	-215.8274	-2649.8240	-1060.6660	-360.2632	-3626.6650	-717.4823	-222.0309	-2784.7510	-1060.7250	-364.8239
F_c	8.1740***	0.2025	2.8199*	8.4062***	2.9711*	0.6287	6.7656***	4.6451**	-	5.7896***	6.6021**	-

Table 5.4: Regression Coefficients: Dispersions of open-ended funds during periods of market stress identified by financial crises

Table 5.4 reports the results of regressions of the following general form: $S_t = \alpha + \beta_1 D_t^{pre} + \beta_2 D_t^{in} + \epsilon_t$,
Where $S = CSAD\ or\ CSSD$; if the market return on day t lies in the extreme lower tail of the distribution, $D_t^{pre} = 1$ if day t is in the pre-crisis period; otherwise it is equal to zero. $D_t^{in} = 1$if day t is in the in-crisis period; otherwise it is equal to zero. The sample period is January 1996 – June 2010, t-statistics are given in parentheses.

Variable definitions:
CSAD: Cross Section Absolute Deviation; **CSSD**: Cross Section Standard Deviation ***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

CSAD	Market return in criteria pre-crisis & crisis period						**CSSD**	Market return in criteria pre-crisis & crisis period					
	Open-ended funds			Closed-end funds				Open-ended funds			Closed-end funds		
	Daily	Weekly	Monthly	Daily	Weekly	Monthly		Daily	Weekly	Monthly	Daily	Weekly	Monthly
α	0.7904*** (23.5038)	0.8977*** (16.3952)	1.2439*** (14.1976)	0.6959*** (29.5799)	1.3699*** (19.2428)	2.6089*** (16.8555)		0.9190*** (25.4029)	1.1030*** (17.6901)	1.6061*** (15.1636)	0.9366*** (31.5884)	1.8689*** (20.2688)	3.6005*** (17.2595)
β_1	-0.1977*** (-4.8714)	-0.1231* (-1.8196)	0.0719 (0.3816)	-0.0824*** (-2.6528)	-0.0112 (-0.1035)	0.5685 (1.2985)		-0.1970*** (-4.5099)	-0.0995 (-1.2377)	0.1825 (0.6687)	-0.0692* (-1.7071)	0.1136 (0.7641)	1.0569* (1.6592)
β_2	0.1149** (2.2234)	0.1450* (1.7741)	0.2785** (2.3758)	0.1404*** (4.0574)	0.3003*** (3.0104)	0.7712*** (3.0355)		0.1483*** (2.6902)	0.2147** (2.3445)	0.4601*** (2.8584)	0.2137*** (0.2137)	0.4604*** (3.1887)	1.1871*** (2.9160)
Adj-R^2	0.0242	0.0191	0.0196	0.0254	0.0221	0.0594		0.0266	0.0225	0.0368	0.0268	0.0277	0.0818
S.D.	0.6470	0.5743	0.6126	0.4363	0.7394	1.2140		0.6677	0.6380	0.8112	0.5622	0.9773	1.7441
SSR	1635.7210	265.1978	68.6706	743.8893	440.1113	269.7190		1742.4260	327.2288	120.4189	1235.3690	768.8001	556.6415
Log LH	-3844.8410	-696.0494	-171.2550	-2304.0110	-901.0584	-298.4845		-3968.4180	-780.8585	-223.4890	-3295.9050	-1126.4110	-365.8668

5.4 Portfolio herding under different market conditions

CCK advise that the appearance of a negative linear or non-linear relationship can be an indicator of herding in the market. The regression model therefore is:

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 (R_{m,t})^2 + \varepsilon_t \tag{5.3}$$

An estimated negative γ_1 or γ_2 in the equation shows the breaking of the fundamental price function, which demonstrates the existence of herd behaviour. Particularly, if the herd behaviour is caused by the sentiment of investors, the degree of herding can be asymmetric in different market conditions.

5.4.1. Herding under Different Market Return Condition

Consistent with CCK's empirical study, the regressions have been run in two such specifications: the up-market, when returns are greater than zero, and the down-market, when returns are less than zero. The regression model is:

$$\begin{aligned} CSAD_t = {} & \alpha * D_1 + \gamma_1^{up} |R_{m,t}| * D_1 + \gamma_2^{up} (R_{m,t})^2 * D_1 + \alpha * D_2 + \gamma_1^{down} |R_{m,t}| * D_2 \\ & + \gamma_2^{down} (R_{m,t})^2 * D_2 + \varepsilon_t \end{aligned} \tag{5.4}$$

where the superscripts up and down refer to positive market returns and negative market returns respectively. $D_1 = 1$when the market has a positive return, i.e. $R_m > 0$; otherwise equals to zero. $D_2 = 1$when the market has a negative return, i.e. $R_m < 0$; otherwise equals to zero[34]. Equation 5.3 and 5.4 are regressed in daily, weekly and monthly frequencies. The estimated results from open-ended and closed-ended funds (Table 5.5A and Table 5.5B respectively) show a very similar feature.

In the daily and weekly data, none of the coefficients in Equation 5.3 is significantly negative, which provides no evidence of herding in the market. When the up and down-

[34] 30-day (week and moth) moving average values have been used as benchmarks for defining the market conditions (Tan et al., 2008). Estimated coefficients suggest very similar results as the zero benchmark, which is available upon request.

market conditions are applied (Equation 5.4), the return dispersion is still an increasing function of the market return regardless of market condition, suggesting the absence of herding behaviour under either condition. The test has not found an asymmetric effect in rising and falling markets.

Different from the daily and weekly data, the monthly γ_1 is not significant demonstrating there is not a linear relation between return dispersion and market return. However, positive significant γ_2 in the unconditional model still gives no clear sign of herd behaviour. When the up- and down conditions are imposed, γ_1^{up} is insignificant, implying the linear relation between does not exist.

Comparing the coefficients in the three time frequencies, values of coefficient, γ_1 reduces while the frequency is lower. It shows that the rates of $CSAD_t$ increasing with $|R_{m,t}|$ decrease when the investment interval increases. This may hint that it is more likely that it takes a longer time for herding behaviour to affect asset prices. This may be the result of the institutional investors undertaking positive feedback trading, i.e. the medium and long term investment strategies involved in buying 'winners' and selling 'losers' (Nofsinger and Sias, 1999).

Table 5.5A: Regression results of CSAD on the linear and squared term of the market portfolio: up and down market for open-ended funds

Table 5.5A reports the results of regressions of the following general form: $CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2(R_{m,t})^2 + \varepsilon_t$, where the whole sample data is estimated. Model with up and down-market conditions is: $CSAD_t = \alpha * D_1 + \gamma_1^{up}|R_{m,t}| * D_1 + \gamma_2^{up}(R_{m,t})^2 * D_1 + \alpha * D_2 + \gamma_1^{down}|R_{m,t}| * D_2 + \gamma_2^{down}(R_{m,t})^2 * D_2 + \varepsilon_t$, where the superscripts up and down refer to market returns going up and market returns going down respectively. $D_1 = 1$when the market has a positive return, i.e. $R_m > 0$; otherwise equals to zero. $D_2 = 1$when the market has a positive return, i.e. $R_m < 0$; otherwise equals to zero. The sample period is January 1996 – June 2010, t-statistics are given in parentheses. The F_1, F_2, and F_3 are the F- statistics of the null hypotheses that $\gamma_1^{up} = \gamma_1^{down}$, $\gamma_2^{up} = \gamma_2^{down}$ and $\alpha^{up} = \alpha^{down}$respectively.

Variable definitions:

CSAD: Cross Section Absolute Deviation; R_m: market returns ***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

CSAD	Daily			Weekly			Monthly		
Coefficients	Whole Sample	Up market (R>0)	Down market (R<0)	Whole Sample	Up market (R>0)	Down market (R<0)	Whole Sample	Up market (R>0)	Down market (R<0)
α	0.4201*** (18.0877)	0.3794*** (16.5588)	0.4591*** (17.1381)	0.6105*** (16.9478)	0.5592*** (11.8385)	0.6841*** (15.1799)	1.1962*** (12.8214)	1.2694*** (8.0363)	1.2336*** (11.7815)
γ_1	0.3821*** (7.5812)	0.3798*** (8.3943)	0.3974*** (7.0071)	0.1420*** (4.1767)	0.1518*** (3.6837)	0.1265*** (2.8913)	-0.0188 (-0.5244)	-0.1238 (-1.5225)	0.0030 (0.0569)
γ_2	0.0211 (1.3926)	0.0396*** (3.4396)	0.0009 (0.0465)	0.0064* (1.7864)	0.0058 (1.6404)	0.0073 (1.2661)	0.0100*** (3.4177)	0.0258** (2.4103)	0.0072** (2.0587)
Adj-R^2	0.3728	0.3845		0.281071	0.2846		0.155972	0.1611	
S.D.	0.5187	0.5138		0.491694	0.4905		0.568373	0.5666	
SSR	1051.329	1031.043		194.3771	192.6922		59.11773	57.7961	
Log LH	-2980.454	-2942.35		-570.6916	-567.1788		-157.3245	-155.222	
F_1		0.069111			0.266067			1.567254	
F_2		3.187010*			0.054611			2.520042	
F_3		6.423717**			4.818478**			0.034013	

Table 5.5B: Regression results of CSAD on the linear and squared term of the market portfolio: up and down market for closed-end funds

Table 5.5B reports the results of regressions of the following general form: $CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2(R_{m,t})^2 + \varepsilon_t$, where the whole sample data is estimated. Model with up and down-market conditions is: $CSAD_t = \alpha * D_1 + \gamma_1^{up}|R_{m,t}| * D_1 + \gamma_2^{up}(R_{m,t})^2 * D_1 + \alpha * D_2 + \gamma_1^{down}|R_{m,t}| * D_2 + \gamma_2^{down}(R_{m,t})^2 * D_2 + \varepsilon_t$, where the superscripts up and down refer to market returns going up and market returns going down respectively. $D_1 = 1$when the market has a positive return, i.e. $R_m > 0$; otherwise equals to zero. $D_2 = 1$when the market has a positive return, i.e. $R_m < 0$; otherwise equals to zero. The sample period is January 1996 – June 2010, t-statistics are given in parentheses. The F_1, F_2, and F_3 are the F- statistics of the null hypotheses that $\gamma_1^{up} = \gamma_1^{down}$, $\gamma_2^{up} = \gamma_2^{down}$ and $\alpha^{up} = \alpha^{down}$respectively.
The model is estimated by OLS with Newey-West standard errors.

Variable definitions:
CSAD: Cross Section Absolute Deviation; R_m: market returns ***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

CSAD	Daily			Weekly			Monthly		
Coefficients	Whole Sample	Up market (R>0)	Down market (R<0)	Whole Sample	Up market (R>0)	Down market (R<0)	Whole Sample	Up market (R>0)	Down market (R<0)
α	0.4033*** (35.7081)	0.3770*** (27.5642)	0.4289*** 35.8838)	1.0017*** (20.1038)	0.9291*** (14.0828)	1.0894*** (22.5387)	2.4463*** (11.7701)	2.8478*** (7.4775)	2.1799*** (12.5037)
γ_1	0.3275*** (14.1747)	0.3303*** (11.8295)	0.3314*** (16.9452)	0.1876*** (3.2311)	0.1822*** (3.2311)	0.1979*** (5.9841)	0.0445 (0.5290)	-0.2358 (-1.2783)	0.2322*** (2.6386)
γ_2	0.0197*** (2.7600)	0.0288*** (3.4899)	0.0097* (1.8594)	0.0159*** (3.3361)	0.0262*** (3.3361)	0.0069* (1.8239)	0.0160* (1.9341)	0.0468** (2.2173)	0.0014 (0.1919)
Adj-R^2	0.6228	0.6292		0.4436	0.4668		0.2141	0.2265	
S.D.	0.2714	0.2691		0.5577	0.5460		1.1097	1.1009	
SSR	287.9637	282.8420		250.4060	239.0890		225.3489	218.1675	
Log LH	-447.7427	-413.0351		-673.2250	-654.5409		-281.7695	-278.7576	
F_1		0.0012			0.0644			4.3728**	
F_2		4.3375**			4.8947**			3.5150*	
F_3		10.2729***			5.3461**			2.4047	

5.4.2. Herding under Different Trading Volume Conditions

Trading volume has been suggested as one of the proxies of investors' sentiment (Baker & Stein, 2004; Kumar & Lee, 2006) and is used as a mean to measure the herding towards particular stocks (Lakonishok et al. 1999; Sia, 2004). Therefore, it can be one of the factors associated with the level of herding. The examinations are conducted in two specifications: up-volume market and down-volume market[35]. The model is:

$$CSAD_t = \alpha^{up-vol}D_1 + \gamma_1^{up-vol}\left|R_{m,t}\right| * D_1 + \gamma_2^{up-vol}{R_{m,t}}^2 * D_1 + \alpha^{dw-vol}D_2 + \gamma_1^{dw-vol}\left|R_{m,t}\right| * D_2 + \gamma_2^{dw-vol}{R_{m,t}}^2 * D_2 + \varepsilon_t \tag{5.5}$$

where the superscripts *up-vol* and *dw-vol* refer to the volume greater or lesser than zero respectively. D_1 = 1 in volume up-market, which is defined as the market when *volume*>0, otherwise is zero;D_2 = 1 in volume down-market, which is defined as the market when *volume*<0, otherwise is zero. Table 5.6 presents the results of the sample estimations.

The estimated results are very similar in both open-ended and closed-end funds. In daily and weekly data, no coefficient of the linear and non-linear factors is significantly negative, implying that the relation between return dispersion and market return that is predicted by rational asset pricing models still holds. This again suggests that no herd behaviour exists regardless of the trading volume conditions. In the monthly interval, when the market trading volume goes down, both coefficients, $\gamma_1^{dw-vol}$and γ_2^{dw-vol}, are not significant. It shows that the return dispersions do not relate to the market returns. Although this is not an indicator of herding behaviour, the broken relationship which is predicted by rational asset price models may suggest herding behaviour when the market is in a volume down time.

[35]As defined in the previous chapter: $Volume = 100 * \ln\left(\frac{level\ volum_t}{level\ volume_{t-1}}\right)$

Table 5.6: Regression results of CSAD on the linear and squared term of the market portfolio: up and down-volume market

Table 5.6 reports the results of regressions of the following general form

$$CSAD_t = \alpha^{up-vol}D_1 + \gamma_1^{up-vol}|R_{m,t}| * D_1 + \gamma_2^{up-vol}R_{m,t}{}^2 * D_1 + \alpha^{dw-vol}D_2 + \gamma_1^{dw-vol}|R_{m,t}| * D_2 + \gamma_2^{dw-vol}R_{m,t}{}^2 * D_2 + \varepsilon_t$$

where the superscripts up-vol and dw-vol refer to the volume greater of lesser than zero respectively. $D_1 = 1$in volume up-market, which is defined as the market when volume > 0, otherwise is zero; $D_2 = 1$ in volume down-market, which is defined as the market when volume < 0, otherwise is zero. The sample period is January 1996 – June 2010. t-statistics are given in parentheses. The F_1 to F_3 are the F- statistics of the null hypotheses that $\gamma_1^{up-vol} = \gamma_1^{dw-vol}$, $\gamma_2^{up-vol} = \gamma_2^{dw-vol}$, , and $\alpha^{up-vol} = \alpha^{dw-vol}$, respectively.
The model is estimated by adjusting the standard errors using the Newey-West procedure

Variable definitions:
CSAD: Cross Section Absolute Deviation; R_m: market returns ***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

CSAD	Open-ended funds			Closed-end funds		
	Daily	Weekly	Monthly	Daily	Weekly	Monthly
$\alpha^{up\text{-}vol}$	0.3999*** (13.8811)	0.6427*** (14.2205)	1.1135*** (8.9756)	0.4096*** (28.7665)	1.0357*** (17.7536)	2.3710*** (8.1185)
$\gamma_1{}^{up\text{-}vol}$	0.3927*** (6.4816)	0.1173*** (3.1607)	0.0228 (0.4231)	0.3236*** (10.9616)	0.1765*** (4.0282)	0.1181 (0.9606)
$\gamma_2{}^{up\text{-}vol}$	0.0123 (0.7093)	0.0069* (1.7881)	0.0081* (1.8451)	0.0175* (1.9592)	0.0127** (2.1818)	0.0106 (0.9819)
$\alpha^{dw\text{--}vol}$	0.4331*** (18.0339)	0.5834*** (12.3781)	1.2201*** (9.8632)	0.3964*** (31.5748)	0.9964*** (16.2657)	2.5326*** (9.5408)
$\gamma_1{}^{dw\text{-}vol}$	0.3768*** (7.4087)	0.1552*** (3.4595)	-0.0076 (-0.1234)	0.3312*** (13.6968)	0.1548*** (3.0826)	-0.0503 (-0.3121)
$\gamma_2{}^{dw\text{-}vol}$	0.0372*** (2.7586)	0.0094 (1.5336)	0.0042 (0.5902)	0.0249*** (4.1238)	0.0297*** (5.0750)	0.0236 (1.2822)
Adj-R^2	0.3780	0.2843	0.1626	0.6239	0.4548	0.2095
S.D.	0.5165	0.4906	0.5661	0.2710	0.5521	1.1129
SSR	1041.8640	192.7726	57.6920	286.8473	244.4746	222.9531
Log LH	-2962.7700	-567.3470	-155.0542	-440.5327	-663.5403	-280.7755
F_1	0.0535	0.5804	0.122861	0.0544	0.1271	0.6266
F_2	1.9748	0.1284	0.193404	0.8366	4.6487**	0.3395
F_3	1.0881	1.0509	0.420950	0.7098	0.2910	0.1962

5.4.3. Herding under Different foreign Market Return Conditions

According to the UK national statistics office, about 40% of UK listed shares are owned by foreign investors, therefore the foreign market changes are expected to have an impact on the UK equity market and consequently influence the UK fund managers decision making. Examination of institutional investor herding under the up-foreign-market and down-foreign-market conditions is conducted by using S&P 500 Composite Index as the representative of foreign market indicator. S&P 500 Composite Index is a capitalisation-weighted index for 500 largest capitalisation companies which are actively traded in the US. The up-foreign market is defined as the returns of foreign market being greater than zero, i.e. $R_{S\&P} > 0$, and the down-foreign market is defined as the returns of foreign market being less than zero, i.e. $R_{S\&P} > 0$. The models applied in the tests are:

$$CSAD_t = \alpha^{up-for} D_1 + \gamma_1^{up-for} \left|R_{m,t}\right| * D_1 + \gamma_2^{up-for} {R_{m,t}}^2 * D_1 + \alpha^{dw-for} D_2 + \gamma_1^{dw-for} \left|R_{m,t}\right| * D_2 + \gamma_2^{dw-for} {R_{m,t}}^2 * D_2 + \varepsilon_t \tag{5.6}$$

where the superscripts *up-for* and *dw-for* refer to the foreign market returns greater or lesser than zero respectively. $D_1 = 1$in up-foreign market, zero otherwise; $D_2 = 1$ in down-foreign market, zero otherwise[36]. The empirical results of estimation are reported in Table 5.7.

The estimated coefficients present very similar pictures for open-ended and closed-end funds in daily and weekly data. γ_1^{up-for} and γ_1^{dw-for} are positive and significant, supporting the prediction of the relationship between dispersion and market made by rational return price models. None of γ_2^{up-for} and γ_2^{dw-for} is significantly negative, which rules out the rate of changing return dispersions decreasing with market returns. This provides no evidence of the existence of herd behaviour in either up-foreign or down-foreign market.

[36] 30-day (week and moth) moving average values have been used as benchmarks for defining the market conditions (Tan et al., 2008). Estimated coefficients suggest very similar results as the zero benchmark, which attached in Appendix.

In the monthly interval, none of the γ is negative and significant, suggesting that no herding behaviour has been found among open-ended and closed-end fund managers. The insignificant of γ_1^{up-for} and γ_1^{dw-for} suggests that linear relation between dispersion and market return does not hold, and the significant of γ_2^{up-for} and γ_2^{dw-for} for open-ended funds indicates that there is a non-linear relation between them. It is notable that estimated γ_1^{up-for} and γ_1^{dw-for} for open-ended funds are negative. However, the relation of dispersion and market cannot easily be normalised on any particular metric, and so the exact magnitude of any specific coefficient dost not have a precise interpretation. It is the signs and relative magnitudes of coefficients on the same variable when compare in the different conditions. This may be a sign that herding is likely to exist in a falling foreign market. It is because that information about foreign financial markets cannot reach the domestic investors at the same speed and level as that of the local market, the sentiment biases are more likely to be involved in investors' decision making. Investor sentiment becomes one possible factor that causes herd behaviour. According to Prospect theory, economic agent's response to loss is more extreme than gain (Tversky and Kahneman, 1986). In the foreign down-market, the negative foreign market returns promote pessimistic expectations about local market return among investors. The fear of making heavier losses than market average motivates fund managers to try to match their portfolio at least in line with the market portfolio.

5.4.4. Herding under Different Market Volatility Conditions

The use of zero as a benchmark to identify whether a market is an up-market or a down market has a limitation. For non-return variables, such as market volatility (σ_{mt}^2) which normally is calculated as the square of the market return in period t and does not have a negative value, Tan et al. (2008) propose the use of moving averages as benchmarks for defining the high or low market conditions. σ_{mt}^2 is regarded as high if on day t it is greater than the previous 30-day moving average[37], and σ_{mt}^2 is characterised low if it is less than the previous 30-day moving average. The same processes apply for weekly and monthly data[38].

[37] 60-day, 90-day and 120-day moving averages are also used to characterize market volatility as high or low.

[38] Because of the data availability, 60, 90 and 120-month moving averages are not applicable.

$$CSAD_t = \alpha^{high} D_1 + \gamma_1^{high} |R_{m,t}| * D_1 + \gamma_2^{high} {R_{m,t}}^2 * D_1 + \alpha^{low} D_2 + \gamma_1^{low} |R_{m,t}| * D_2 + \gamma_2^{low} {R_{m,t}}^2 * D_2 + \varepsilon_t \tag{5.7}$$

where the superscripts $high$ and low refer $\sigma_m^2 > \sigma_m^{2,*}$ and $\sigma_m^2 < \sigma_m^{2,*}$respectively, $\sigma_m^{2,*}$=30 day (week or month) moving average. $D_1 = 1$ when $\sigma_m^2 > \sigma_m^{2,*}$, zero otherwise; $D_2 = 1$ when $\sigma_m^2 > \sigma_m^{2,*}$zero otherwise. The estimated results are reported in Table 5.8.

The estimated coefficients from both open-ended and closed-end funds exhibit very similar results. There is no significant negative coefficient to provide evidence for herding behaviour in all three frequencies of data. Particularly, the positive and significant γ_1s and insignificant γ_2 in daily data demonstrate that return dispersion is an increasing linear function of market return regardless of the level of market volatility. In the weekly and monthly data, some of the coefficients have negative values which may imply a decreasing relation between return dispersion. Especially, the estimated negative coefficients are more likely to appear in the low volatility period. This may suggest that institutional investors are likely to herd in the medium and long term when the market is less volatile. This can be explained in that the low volatile time is normally the period when less public information in the market. Investment decisions are made according to private information. Institutional investors have more resource to collect and analyse information of their peers and are therefore more likely to herd on each other's portfolio. Statistically however, the estimated coefficients are not significant negative which suggests that the herding evidence is not found.

The analysis relation between cross-section mutual fund return dispersion and market return shows that fund managers do not herd in a short investment interval, but may herd when market volatility is low in the medium or long investment interval. However, there is no significant sign suggesting herding behaviour in both high and low volatility markets.

Table 5.7: Regression results of CSAD on the linear and squared term of the market portfolio: up and down foreign market

Table 5.7 reports the results of regressions of the following general form

$$CSAD_t = \alpha^{up-for} D_1 + \gamma_1^{up-for} |R_{m,t}| * D_1 + \gamma_2^{up-for} R_{m,t}{}^2 * D_1 + \alpha^{dw-for} D_2 + \gamma_1^{dw-for} |R_{m,t}| * D_2 + \gamma_2^{dw-for} R_{m,t}{}^2 * D_2 + \varepsilon_t$$

where the superscripts *up-for* and *dw-for* refer to the foreign market returns greater of lesser than zero respectively. $D_1 = 1$in up-foreign market, zero otherwise; $D_2 = 1$ in down-foreign market, zero otherwise. The sample period is January 1996 – June 2010. t-statistics are given in parentheses. The F_1 to F_3 are the F- statistics of the null hypotheses that $\gamma_1^{up-for} = \gamma_1^{dw-for}$, $\gamma_2^{up-for} = \gamma_2^{dw-for}$, , and $\alpha^{up-for} = \alpha^{\mathrm{dw-for}}$, respectively.

The model is estimated by adjusting the standard errors using the Newey-West procedure

Variable definitions:

CSAD: Cross Section Absolute Deviation; R_m: market returns ***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

CSAD	Open-ended funds			Closed-end funds		
	Daily	Weekly	Monthly	Daily	Weekly	Monthly
$\alpha^{up\text{-}for}$	0.4328*** (18.8995)	0.5484*** (11.8023)	1.1299*** (10.6630)	0.3825*** (32.9820)	0.9724*** (15.2819)	2.2675*** (9.6785)
$\gamma_1{}^{up\text{-}for}$	0.3007*** (7.2357)	0.1616*** (3.9563)	-0.0332 (-0.5143)	0.3319*** (15.0130)	0.1649*** (3.1097)	0.0933 (0.6596)
$\gamma_2{}^{up\text{-}for}$	0.0435*** (3.6017)	0.0039 (1.3380)	0.0159* (1.7926)	0.0223*** (3.3389)	0.0266*** (3.6293)	0.0118 (0.7311)
$\alpha^{dw\text{--}for}$	0.4180*** (14.1041)	0.6966*** (14.3613)	1.3667*** (1.3667)	0.4355*** (26.8808)	1.0300*** (20.0511)	2.6821*** (8.2882)
$\gamma_1{}^{dw\text{-}for}$	0.4519*** (6.9316)	0.1145** (2.3646)	-0.0660 (-1.1739)	0.3089*** (8.5486)	0.2205*** (6.4805)	0.0109 (0.0910)
$\gamma_2{}^{dw\text{-}for}$	-0.0016 (-0.0946)	0.0092 (1.4076)	0.0123*** (3.0241)	0.0195* (1.7419)	0.0056 (1.4924)	0.0171 (1.6302)
Adj-R^2	0.3135	0.2860	0.1604	0.5376	0.4587	0.2111
S.D.	0.5427	0.4900	0.5669	0.3005	0.5501	1.1118
SSR	1149.904	192.3110	57.8467	352.6453	242.7106	222.4922
Log LH	-3155.713	-566.3798	-155.3032	-844.3680	-660.6147	-280.5831
F_1	3.7107*	0.8153	0.1449	0.3249	0.9497	0.1704
F_2	5.1078**	0.6469	0.1292	0.0528	6.6747**	0.0622
F_3	0.1653	6.5308**	1.7703	8.9553***	0.6719	1.1047

Table 5.8: Regression results of CSAD on the linear and squared term of the market portfolio: high- and low-market volatility under moving average 30

Table 5.8 reports the results of regressions of the following general form:

$$CSAD_t = \alpha^{high} D_1 + \gamma_1^{high} |R_{m,t}| * D_1 + \gamma_2^{high} R_{m,t}{}^2 * D_1 + \alpha^{low} D_2 + \gamma_1^{low} |R_{m,t}| * D_2 + \gamma_2^{low} R_{m,t}{}^2 * D_2 + \varepsilon_t$$

where the superscripts *high* and *low* refer $\sigma_m^2 > \sigma_m^{2,*}$ and $\sigma_m^2 < \sigma_m^{2,*}$ respectively, $\sigma_m^{2,*}$=30 day (week or month) moving average. $D_1 = 1$ when $\sigma_m^2 > \sigma_m^{2,*}$, zero otherwise; $D_2 = 1$ when $\sigma_m^2 > \sigma_m^{2,*}$ zero otherwise. The sample period is January 1996 – June 2010, t-statistics are given in parentheses. The F_1, F_2, and F_3 are the F- statistics of the null hypotheses that $\gamma_1^{high} = \gamma_1^{low}$, $\gamma_2^{high} = \gamma_2^{low}$ and $\alpha^{high} = \alpha^{low}$ respectively.
The model is estimated by OLS method with adjusting the standard errors using the Newey-West procedure

Variable definitions:

CSAD: Cross Section Absolute Deviation; R_m: market returns ***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

CSAD	Open-ended funds			Closed-end funds		
	Daily	Weekly	Monthly	Daily	Weekly	Monthly
α^{high}	0.1212 (1.6075)	0.1640 (1.5674)	0.6282* (1.8820)	0.1882*** (5.2408)	0.5613*** (4.0995)	1.0191 (1.5817)
γ_1^{high}	0.5591*** (6.2262)	0.3096*** (5.6198)	0.1469 (1.4061)	0.4741*** (11.2194)	0.3441*** (4.6269)	0.4680** (2.1532)
γ_2^{high}	0.0002 (0.0115)	-0.0065 (-1.4450)	-0.0004 (-0.0584)	0.0013 (0.1386)	0.0042 (0.5260)	-0.0107 (-0.7460)
α^{low}	0.4270*** (14.8555)	0.7234*** (12.1490)	1.3567*** (10.0090)	0.4278*** (32.4585)	1.0964*** (13.4395)	2.7340*** (7.5140)
γ_1^{low}	0.4102*** (3.3518)	-0.0785 (-0.5486)	-0.2260 (-1.4355)	0.2881*** (6.1575)	-0.0060 (-0.0328)	-0.2810 (-0.7761)
γ_2^{low}	0.0804 (0.9604)	0.0969 (1.4824)	0.0574 (1.5353)	0.0622** (2.3409)	0.1047 (1.2905)	0.0823 (1.0312)
Adj-R^2	0.3907	0.3111	0.1620	0.6354	0.4637	0.2221
S.D.	0.5112	0.4813	0.5663	0.2668	0.5476	1.1041
SSR	1020.624	185.5632	57.7319	278.0508	240.4587	219.4067
Log LH	-2922.491	-551.9674	-155.1184	-379.6261	-656.8488	-279.2843
F_1	0.7050	5.2822**	3.1908*	7.4466***	2.6757	2.5848
F_2	0.7012	2.4068	2.1204	4.3089**	1.4449	1.2283
F_3	12.2295***	17.9074***	3.8553***	35.7342***	10.2773***	4.7412**

5.4.5. Portfolio herding in different financial crisis stages

In the last section, the financial crisis criterion was introduced as the ability to identify market turbulence periods, and the study indicates that fund managers are more likely to follow the crowd during the pre-crisis period in the short to medium terms. Therefore, the relation between return dispersion and market return under financial crisis conditions is examined in order to reveal the portfolio herd behaviour:

$$
\begin{aligned}
CSAD_t = \alpha^{no-cri} D_1 + \gamma_1^{no-cri} \left|R_{m,t}\right| * D_1 + \gamma_2^{no-cri} {R_{m,t}}^2 * D_1 + \alpha^{pre-cri} D_2 \\
+ \gamma_1^{pre-cri} \left|R_{m,t}\right| * D_2 + \gamma_2^{pre-cri} {R_{m,t}}^2 * D_2 + \alpha^{in-cri} D_3 \\
+ \gamma_1^{in-cri} \left|R_{m,t}\right| * D_3 + \gamma_2^{in-cri} {R_{m,t}}^2 * D_3 + \varepsilon_t
\end{aligned}
\tag{5.8}
$$

where the superscripts no-cri refers no-crisis period, pre-cri refers pre-crisis period and in-cri refers in the crisis period. $D_1 = 1$in the no-crisis period, zero otherwise; $D_2 = 1$ in the pre-crisis, zero otherwise; $D_3 = 1$ in the crisis period, zero otherwise. The absolute value of market return, $R_{m,t}$, is used to facilitate the comparisons of the coefficients of the linear term in the non-crisis period, pre-crisis period, and post-crisis period. The estimated results are shown in Table 5.9.

The estimated coefficients from both open-ended and closed-end funds exhibited very similar stories. None of the coefficients is significantly negative to demonstrate that return dispersion is a decreasing function of market return in different stages of the financial crisis in all frequencies of data. No herding evidence, therefore, can be found in the normal, pre-crisis or in-crisis period. This is different from the results using CH approach which suggests herding behaviour in the pre-crisis period. CH approach suggests that return dispersion in the pre-crisis period, on average, is less than that in the normal period, but CCK approach indicates that return dispersion in pre-crisis is still not a decreasing function of the market return. The null of $\gamma_1^{\mathrm{no-cri}} = \gamma_1^{\mathrm{pre-cri}}$ is rejected at the 5% significant level in the daily data, implying a lesser degree of increasing relationship between return dispersion and market return in the pre-crisis period. This may be a sign of a very low degree of herding behaviour in the pre-crisis period.

Looking at the coefficients amongst the different time intervals, there is no clear evidence of herding behaviour under different crisis conditions. It is more likely that herding behaviour appears in the longer time horizon. For example, estimated values of γ_1s in the pre-crisis period in monthly interval are negative, however they are not statistically significant. This phenomenon can be explained in that the performances of fund managers are more like to be appraised in a relatively longer time interval. In order to keep in line with their peers and protect their reputation, managers try to match their portfolios to the market average at a similar frequency to that of the performances being evaluated against.

The investigations of institutional herding behaviour by using cross-section return dispersion as a measure have not provided significant evidence of fund managers herding behaviour by using CCK approach. None of the estimated coefficients is significantly negative to demonstrate that return dispersion is a decreasing (or increasing but in a decreasing rate) function of absolute term of market return. Particularly, the estimated coefficients by daily data indicate that return dispersions increase alongside absolute market returns regardless of market condition. This suggests that fund managers do not herd in the short investment interval. Estimated coefficients by using weekly data, however, indicate that there is neither linear nor non-linear relation between return dispersion and market return when market volatility is low. This may give a hint of some possibilities of the existence of herding behaviour. The sign gets stronger when using monthly data. This may suggest that fund managers' are likely herd in a long investment interval. It may because the performance of fund managers is normally measured in a relatively longer time interval, for example monthly. In order to be in line with the benchmark return or catch up with peers, fund managers mimic others portfolio to prevent an unfavoured result.

This is opposite to what CH and Lao and Singh (2011) suggested: that herding is likely to be a short-life activity if it is caused by investor sentiment. They demonstrate that investors are more likely to put more weight on the noise information and make decisions with psychological biases when market uncertainty is generated by lack of information in a short run, and in medium and long runs, this uncertainty is less likely to have effects in sophisticated fund managers' decision making, therefore, sentiment caused herding dies down. However, the principle-agent problem may affect fund managers' investment decision in the long run. Career prospects, financial benefits, and reputational concerns are taken as factors into their investment decisions. These motivate them to be a 'winner' in the market not to be a 'loser', and the market condition is now not a factor that encourages them to herd more or less. The findings of herding under foreign market conditions, in turn, confirm the hypothesis that the US equity market has an influence on UK fund managers' decision making.

Table 5.9: Regression results of CSAD on the linear and squared term of the market portfolio in different crisis stages

Table 5.9 reports the results of regressions of the following general form

$$CSAD_t = \alpha^{no-cri}D_1 + \gamma_1^{no-cri}|R_{m,t}| * D_1 + \gamma_2^{no-cri}R_{m,t}{}^2 * D_1 + \alpha^{pre-cri}D_2 + \gamma_1^{pre-cri}|R_{m,t}| * D_2 + \gamma_2^{pre-cri}R_{m,t}{}^2 * D_2 + \alpha^{in-cri}D_3 + \gamma_1^{in-cri}|R_{m,t}| * D_3 + \gamma_2^{in-cri}R_{m,t}{}^2 * D_3 + \varepsilon_t$$

where $D_1 = 1$ in no-crisis period, otherwise is zero; $D_2 = 1$ in the pre-crisis, otherwise is zero; $D_3 = 1$ in crisis period, otherwise is zero. The absolute value of market return, $R_{m,t}$, is used to facilitate the comparisons of the coefficients of the linear term in the non-crisis period, pre-crisis period, and post-crisis period. The sample period is January 1996 – June 2010. t-statistics are given in parentheses.

The F_1 to F_6 are the F- statistics of the null hypotheses that $\gamma_1^{pre-cri} = \gamma_1^{in-cri}$, $\gamma_1^{no-cri} = \gamma_1^{pre-cri}$,$\gamma_1^{no-cri} = \gamma_1^{in-cri}$, $\gamma_2^{pre-cri} = \gamma_2^{in-cri}$, $\gamma_2^{no-cri} = \gamma_2^{pre-cri}$, and $\gamma_2^{no-cri} = \gamma_2^{in-cri}$, respectively.

Variable definitions:

CSAD: Cross Section Absolute Deviation; R_m: market returns ***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

CSAD	Open-ended funds			Closed-end funds		
	Daily	Weekly	Monthly	Daily	Weekly	Monthly
α^{no-cri}	0.4157*** (13.4658)	0.5341*** (11.9895)	1.1723*** (9.5416)	0.3708*** (27.7215)	0.8966*** (16.6386)	2.1251*** (11.0738)
γ_1^{no-cri}	0.4086*** (6.3716)	0.1946*** (4.0568)	-0.0531 (-1.0220)	0.3514*** (12.6777)	0.2079*** (3.3135)	0.0607 (0.5473)
γ_2^{no-cri}	0.0175 (1.0274)	0.0022 (0.4790)	0.0128*** (3.5390)	0.0168** (2.1655)	0.0155** (2.1091)	0.0137* (1.7494)
$\alpha^{pre-cri}$	0.4004*** (18.2867)	0.7846*** (9.7069)	1.3207*** (5.9320)	0.4286*** (20.7699)	1.1111*** (8.5324)	2.9047*** (6.0947)
$\gamma_1^{pre-cri}$	0.1996*** (3.5502)	-0.0872 (-1.1851)	-0.1905 (-1.5473)	0.1779*** (2.8627)	0.0959 (0.7248)	-0.2585 (-1.3977)
$\gamma_2^{pre-cri}$	0.0935*** (3.2759)	0.0383** (2.3527)	0.0435*** (2.9990)	0.1028*** (2.7138)	0.0435 (1.3184)	0.0814*** (3.5676)
α^{in-cri}	0.5395*** (11.1442)	0.7150*** (9.7588)	1.3384*** (7.6954)	0.5699*** (20.2888)	1.2852*** (9.3665)	3.2595*** (10.2306)
γ_1^{in-cri}	0.3476*** (3.9968)	0.1987** (2.5116)	0.0884 (0.1874)	0.2017*** (4.3002)	0.1738* (1.7817)	-0.1143 (-0.9286)
γ_2^{in-cri}	0.0102 (0.3738)	-0.0143 (-1.0498)	-0.0068 (-1.2360)	0.0379*** (2.7668)	0.0016 (0.1071)	0.0261* (1.8622)
Adj-R^2	0.3803	0.29926	0.2229	0.6335	0.4627	0.3355
S.D.	0.5156	0.48543	0.5454	0.2675	0.5481	1.0204
SSR	1037.1610	188.04480	52.6485	279.2854	240.0120	184.3023
Log LH	-2953.9220	-557.32780	-146.5464	-388.2899	-656.0976	-263.0698
F_1	2.0373	6.9518***	3.4302*	0.0935	0.2357	0.4215
F_2	6.0178**	10.2536***	1.0639	6.4991**	0.5880	2.4546
F_3	0.3189	0.0020	2.6253	7.5495***	0.0863	1.3153
F_4			8.8930***	2.6049	1.3504	4.4096**
F_5			4.2429**	4.9527**	0.6891	8.0056***
F_6			8.1846***	1.8038	0.6657	0.6079

5.5 Overlapping and non-overlapping data

The weekly and monthly analysis so far used non-overlapping data. Hansen and Hodrick (1980) state that the overlapping of observations can create a moving average error term and thus Ordinary Least Squares parameter estimates would be inefficient and hypothesis tests biased. One of the methods to deal with the overlapping observations problem is to use a reduced sample in which no observation is overlapped, but this means having to sacrifice observations in the process. However, according to Harri and Brorsen (2009), the majority of articles in finance now use overlapping data. They point out that the using of overlapping data can be for either economic reasons or statistical ones. One of the statistical reasons for using overlapping data is that the information discarded through using non-overlapping observation may lead to the estimation being inefficient. For example, in this study, for a 15.5-year period of monthly data, the number of overlapping observations that can be used in estimation is 3889 instead of 186 of non-overlapping observations. In order to deal with the overlapping observations problem, several heteroskedasticity and autocovariance consistent (HAC) estimators, such as Hansen and Hodrick (1980), Newey-West (1987) and Andrews and Monahan (1990), have been constructed to provide asymptotically valid hypothesis tests. In order to add the robustness for the studies in previous sections, the regressions are re-conducted by using the overlapping data and estimated by applying the Newey-West estimator[39].

Table 5.10 to Table 5.14 present the results that overlapping weekly and monthly data are applied in regression to examine herd behaviour under financial crisis periods and different market conditions respectively. Generally, comparing the results to their corresponding non-overlapping regressions (Table 5.4 – Table 5.9), the estimation results are fairly similar. The coefficients and hypothesis tests under both overlapping and non-overlapping regressions provide some evidence of herd behaviour during market unrest periods and under different market conditions.

When the examination of herding in the market stress period is conducted by using the financial crises as the criteria (Table 5.10), estimated coefficients from overlapping data present similar pictures to those from non-overlapping data. The coefficients for pre-

[39] Only overlapping data of open-ended funds has been reported in this study since the results of closed-end funds are very similar to open-ended funds.

crisis are negative and significant and the coefficients for in-crisis are positive and significant in weekly interval, suggesting herding behaviour in pre-crisis period but not in crisis period. The monthly estimated coefficients are not significant during pre-crisis period and significant positive during in-crisis period, which is similar to estimations from non-overlapping data.

The overlapping regressions of herd behaviour under varying market conditions are also fairly consistent with those in non-overlapping regressions. For example, no coefficient is significantly negative under up- and down-market conditions (Table 5.11), which suggests no herding evidence regardless of the market condition. These agree with the results estimated from non-overlapping data (see Table 5.5A). However, some differences still exist. For instance, in the monthly up-market ($R_m > 0$), estimated γ_1^{up} is positive, but not significant, which gives no hint of herding in the up-market which is different from the result under non-overlapping regression. γ_2^{dw} under overlapping regression has a negative value implying a possibility of herd behaviour, but it is rejected by the significance test.

The estimation of herding under different financial crisis stages in both weekly and monthly interval displays very similar patterns in overlapping regression (see Table 5.14) and non-overlapping regression (Table 5.9). Differences, however, also exist, for example, in the weekly interval, the coefficient, γ_1^{in-cri}, is not significant and γ_2^{in-cri} is positive significant in overlapping regression. This suggests that a non-linear rather than linear relation between dispersion and market return, indicating herd behaviour may exist in the post-crisis period. This is different from the estimated coefficients by using non-overlapping data, $\gamma_1^{in-cris}$ is significant positive and $\gamma_2^{in-cris}$ is insignificant, indicating no herding evidence in the post-crisis period.

Correspondingly, the overlapping regressions with different trading volume regimes (Table 5.12 Vs Table 5.6) and different foreign market conditions (Table 5.13 Vs Table 5.7) all display similar features to those from non-overlapping estimations. There are still differences appearing in the results, particularly in the monthly interval. This may be because the moving average error term created by overlapping data in the monthly interval is not erased by the estimation method (Newey-West HAC Standard Errors & Covariance in this study) and thus the parameter estimates would be inefficient and hypothesis tests biased.

Table 5.10: Overlapping Regression Coefficients: Dispersions during periods of market stress identified by financial crises for open-ended funds

Table 5.10 reports the results of regressions of the following general form: $S_t = \alpha + \beta_1 D_t^{pre} + \beta_2 D_t^{in} + \epsilon_t$,

Where $S = CSAD\ or\ CSSD$; if the market return on day t lies in the extreme lower tail of the distribution, $D_t^{pre} = 1$ if day t is in the pre-crisis period; otherwise it is equal to zero. $D_t^{in} = 1$if day t is in the in-crisis period; otherwise it is equal to zero.The F_c statistics test the null hypotheses that $\beta_1 = \beta_2$. The sample period is January 1996 – June 2010, t-statistics are given in parentheses.

Variable definitions:
CSAD: Cross Section Absolute Deviation; **CSSD**: Cross Section Standard Deviation ***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

CSAD	Market return in criteria pre- & in-crisis period		**CSSD**	Market return in criteria pre- & in-crisis period	
	Weekly	Monthly		Weekly	Monthly
α	0.9531*** (26.3263)	1.3666*** (33.8257)		1.1517*** (28.4015)	1.7541*** (35.3282)
β_1	-0.1368*** (-3.0079)	0.0012 (0.0152)		-0.1076** (-2.0073)	0.1158 (1.0441)
β_2	0.1762*** (3.4181)	0.3317*** (4.9588)		0.2436*** (4.1266)	0.5013*** (5.3035)
Adj-R^2	0.0203	0.0273		0.0231	0.0375
S.D.	0.6818	0.7591		0.7342	0.9446
SSR	1876.2490	2239.7690		2175.4620	3468.2560
Log LH	-4182.6970	-4445.9600		-4481.5150	-5296.4680
F_c	46.6617***	15.8311***		40.2952***	9.1712***

Table 5.11: Overlapping regression results of CSAD on the linear and squared term of the market portfolio: up and down marketfor open-ended funds

Table 5.11 reports the results of regressions of the following general form: $CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2(R_{m,t})^2 + \varepsilon_t$,

where the whole sample data is estimated.

Model with up and down-market conditions is:
$CSAD_t = \alpha * D_1 + \gamma_1^{up}|R_{m,t}| * D_1 + \gamma_2^{up}(R_{m,t})^2 * D_1 + \alpha * D_2 + \gamma_1^{down}|R_{m,t}| * D_2 + \gamma_2^{down}(R_{m,t})^2 * D_2 + \varepsilon_t$,

where the superscripts up and down refer to market returns going up and market returns going down respectively. $D_1 =$ 1when the market has a positive return, i.e. $R_m > 0$; otherwise equals to zero. $D_2 =$ 1when the market has a positive return, i.e. $R_m < 0$; otherwise equals to zero. The sample period is January 1996 – June 2010, t-statistics are given in parentheses. The F_1, F_2, and F_3 are the F- statistics of the null hypotheses that $\gamma_1^{up} = \gamma_1^{down}$, $\gamma_2^{up} = \gamma_2^{down}$ and $\alpha^{up} = \alpha^{down}$respectively.

Variable definitions:
CSAD: Cross Section Absolute Deviation; R_m: market returns ***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

CSAD	Weekly				Monthly		
Coefficients	Whole Sample	Up market (R>0)	Down market (R<0)		Whole Sample	Up market (R>0)	Down market (R<0)
α	0.6582*** (28.6164)	0.6164*** (19.6157)	0.7220*** (26.6208)		1.1228*** (30.5880)	1.1313*** (23.1838)	1.2708*** (25.9608)
γ_1	0.1448*** (6.9491)	0.1436*** (4.4151)	0.1351*** (6.0615)		0.0800*** (5.6028)	0.0030 (0.1083)	0.0854*** (5.2478)
γ_2	0.0069** (2.4019)	0.0091* (1.8746)	0.0064** (2.0924)		0.0008 (0.8747)	0.0097*** (3.6512)	-0.0003 (-0.3672)
F_1		0.0511				6.8495***	
F_2		0.2191				13.226***	
F_3		7.9928***				5.1387**	

Table 5.12: Overlapping regression results of CSAD on the linear and squared term of the market portfolio: up and down volume market for open-ended funds

Table 5.12 reports the results of regressions of the following general form

$$CSAD_t = \alpha^{up-vol}D_1 + \gamma_1^{up-vol}|R_{m,t}| * D_1 + \gamma_2^{up-vol}R_{m,t}{}^2 * D_1 + \alpha^{dw-vol}D_2 + \gamma_1^{dw-vol}|R_{m,t}| * D_2 + \gamma_2^{dw-vol}R_{m,t}{}^2 * D_2 + \varepsilon_t$$

where the superscripts up-vol and dw-vol refer to the volume greater of lesser than zero respectively. $\mathrm{D}_1 = 1$ in volume up-market, which is defined as the market when volume > 0, otherwise is zero; $\mathrm{D}_2 = 1$ in volume down-market, which is defined as the market when volume < 0, otherwise is zero. The sample period is January 1996 – June 2010. t-statistics are given in parentheses. The F_1 to F_3 are the F- statistics of the null hypotheses that $\gamma_1^{up-vol} = \gamma_1^{dw-vol}$, $\gamma_2^{up-vol} = \gamma_2^{dw-vol}$, , and $\alpha^{up-vol} = \alpha^{\mathrm{dw-vol}}$, respectively.

The model is estimated by adjusting the standard errors using the Newey-West procedure

Variable definitions:

CSAD: Cross Section Absolute Deviation; R_m: market returns ***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

CSAD	Weekly		Monthly	
	Coefficients	t-statistic	Coefficients	t-statistic
α^{up-vol}	0.6679***	23.7066	1.0838***	27.4422
γ_1^{up-vol}	0.1389***	6.2695	0.0964***	6.2943
γ_2^{up-vol}	0.0066**	2.1874	-6.43E-05	-0.0749
$\alpha^{dw--vol}$	0.6559***	22.3977	1.1718***	24.6544
γ_1^{dw-vol}	0.1405***	4.8316	0.0568***	2.8885
γ_2^{dw-vol}	0.0095**	2.3274	0.0022	1.4921
F_1	0.0025		4.2278**	
F_2	0.3960		3.1025*	
F_3	0.1166		3.5805*	

Table 5.13: Overlapping regression results of CSAD on the linear and squared term of the market portfolio: up and down foreign market for open-ended funds

Table 5.13 reports the results of regressions of the following general form

$$CSAD_t = \alpha^{up-for} D_1 + \gamma_1^{up-for}|R_{m,t}| * D_1 + \gamma_2^{up-for} R_{m,t}{}^2 * D_1 + \alpha^{dw-for} D_2 + \gamma_1^{dw-for}|R_{m,t}| * D_2 + \gamma_2^{dw-for} R_{m,t}{}^2 * D_2 + \varepsilon_t$$

where the superscripts *up-for* and *dw-for* refer to the foreign market returns greater of lesser than zero respectively. $D_1 = 1$in up-foreign market, zero otherwise; $D_2 = 1$ in down-foreign market, zero otherwise. The sample period is January 1996 – June 2010. t-statistics are given in parentheses. The F_1 to F_3 are the F- statistics of the null hypotheses that $\gamma_1^{up-for} = \gamma_1^{dw-for}$, $\gamma_2^{up-for} = \gamma_2^{dw-for}$, , and $\alpha^{up-for} = \alpha^{dw-for}$, respectively.

The model is estimated by adjusting the standard errors using the Newey-West procedure

Variable definitions:

CSAD: Cross Section Absolute Deviation; R_m: market returns ***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

CSAD	Weekly		Monthly	
	Coefficients	t-statistic	Coefficients	t-statistic
$\alpha^{up\text{-}for}$	0.6227***	20.0453	1.1979***	24.5307
$\gamma_1^{up\text{-}for}$	0.1392***	4.5694	-0.01432	-0.5797
$\gamma_2^{up\text{-}for}$	0.0085*	1.9401	0.0104***	4.2593
$\alpha^{dw\text{-}\text{-}for}$	0.7106***	24.2275	1.1938***	23.8341
$\gamma_1^{dw\text{-}for}$	0.1435***	6.2274	0.0997***	5.9041
$\gamma_2^{dw\text{-}for}$	0.0062**	2.0282	-0.0007	-0.9639
F_1	0.0147		15.326***	
F_2	0.2023		19.576***	
F_3	4.8981**		0.0041	

Table 5.14: Overlapping regression results of CSAD on the linear and squared term of the market portfolio: different crisis stages for open-ended funds

Table 5.14 reports the results of regressions of the following general form

$$CSAD_t = \alpha^{no-cri}D_1 + \gamma_1^{no-cri}|R_{m,t}| * D_1 + \gamma_2^{no-cri}R_{m,t}^{\ 2} * D_1 + \alpha^{pre-cri}D_2 + \gamma_1^{pre-cri}|R_{m,t}| * D_2 + \gamma_2^{pre-cri}R_{m,t}^{\ 2} * D_2 + \alpha^{in-cri}D_3 + \gamma_1^{in-cri}|R_{m,t}| * D_3 + \gamma_2^{in-cri}R_{m,t}^{\ 2} * D_3 + \varepsilon_t$$

where $D_1 = 1$ in no-crisis period, otherwise is zero; $D_2 = 1$ in the pre-crisis, otherwise is zero; $D_3 = 1$ in crisis period, otherwise is zero. The absolute value of market return, $R_{m,t}$, is used to facilitate the comparisons of the coefficients of the linear term in the non-crisis period, pre-crisis period, and post-crisis period. The sample period is January 1996 – June 2010. t-statistics are given in parentheses.

The F_1 to F_6 are the F- statistics of the null hypotheses that $\gamma_1^{pre-cri} = \gamma_1^{in-cri}$, $\gamma_1^{no-cri} = \gamma_1^{in-cri}$,$\gamma_1^{no-cri} = \gamma_1^{in-cri}$, $\gamma_2^{pre-cri} = \gamma_2^{in-cri}$, $\gamma_2^{no-cri} = \gamma_2^{pre-cri}$, and $\gamma_2^{no-cri} = \gamma_2^{in-cri}$, respectively.

Variable definitions:

CSAD: Cross Section Absolute Deviation; R_m: market returns ***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

CSAD	Weekly		Monthly
α^{no-cri}	0.6026*** (22.5090)		1.0377*** (23.5839)
γ_1^{no-cri}	0.1786*** (7.2959)		0.0843*** (4.5839)
γ_2^{no-cri}	0.0047* (1.6746)		0.0008 (0.7438)
$\alpha^{pre-cri}$	0.6949*** (18.1920)		1.2226*** (16.0463)
$\gamma_1^{pre-cri}$	0.0276 (0.7424)		-0.0259 (-0.4902)
$\gamma_2^{pre-cri}$	0.0242*** (2.8413)		0.0178*** (2.8276)
α^{in-cri}	0.9478*** (17.0884)		1.5096*** (14.2496)
γ_1^{in-cri}	0.0399 (1.0615)		0.0425 (1.2958)
γ_2^{in-cri}	0.0142** (2.1781)		0.0003 (0.1078)
F_1	0.0537		1.2259
F_2	11.5047***		3.8845**
F_3	9.5570***		1.2388
F_4	0.8611		6.6807***
F_5	4.7173**		7.0644***
F_6	1.7905		0.0381

5.6 CAPM Beta dispersion and portfolio herding

Hwang & Salmon (2004) (HS) suggest that the perception of risk return relationship of assets may be distorted if investors are influenced by behavioural biases, and it is possible that betas of the stocks will deviate from their equilibrium values. Thus the beta of a stock may change with fluctuations in investors' sentiment, and the cross-sectional dispersion of betas is expected to be smaller in the presence of herd behaviour. Empirical evidence shows that the risk-return relationship of UK unit trusts does vary over time (Black, Fraser and Power, 1992). Therefore, herding can also be tested by investigating the dispersion of the betas of UK open-ended funds.

5.6.1. OLS estimated betas

In accordance with HS approach, weekly and monthly betas are estimated by OLS from daily returns by applying the market model:

$$r_{itd} = \alpha + \beta_{itj}^{b} r_{mtd} + \varepsilon_{itd} \qquad j = w, m \tag{5.9}$$

where r_{itd} represent the return of fund portfolio i at date t, r_{mtd} is market return at date t, and β_{itw}^{b} is the weekly and β_{itm}^{b} is the monthly beta estimated by using daily data over weekly (monthly) interval. The cross-sectional standard deviation of the estimated betas is then calculated as:

$$Std_c\left(\beta_t^b\right) = \sqrt{\frac{\sum_{i=1}^{N_t}\left(\beta_{itj}^{b} - \overline{\beta_t^b}\right)^2}{N_t}} \tag{5.10}$$

where$\overline{\beta_t^b}$ is the cross-section average beta at week (month) t.

Since herding can be a result of investors adjusting their investment to the market fundamentals and macroeconomic information, more tests are designed to detect whether herd behaviour is led by such factors. HS propose to add more independent variables in the measurement equation. The argument is that, after these variables are included, a significant H_{mt} indicates herding still remaining as a factor to explain the changes in the $Std_c(\beta^b_{imt})$. The analysis is therefore conducted in 3 different stages.

The first stage is to examine herding of mutual fund in a basic model which does not take fundamental market and macroeconomic factors into account. This is to estimate the state space model of equation (4.10) and (4.11):

$$log[Std_c(\beta^b_{imt})] = \mu_m + H_{mt} + v_{mt}$$

$$H_{mt}=\phi_m H_{mt-1} + \eta_{mt}$$

where $Std_c(\beta^b_{imt})$ represent the standard deviation of UK fund betas, H_{mt} is the unobservable herding parameter.

The second stage is to examine whether herding is caused by fundamental market factors. This is done by adding market volatility (σ_{mt}), market return (R_{mt}) and foreign market return (represented by return of S&P) into the measurement equation of the state space model. The foreign market return (R^F_{mt}) is included as an independent variable because previous studies suggest that foreign market return and investors' sentiment have an impact on the UK market and investors' behaviour (Verma & Soydemir, 2006). The basic state space model above is amended into model 2 as:

$$log[Std_c(\beta^b_{imt})] = \mu_m + H_{mt} + \theta_{m1} log\sigma_{mt} + \theta_{m2} R_{mt} + \theta_{m3} R^F_{mt} + v_{mt} \tag{5.11}$$

$$H_{mt}=\phi_m H_{mt-1} + \eta_{mt} \tag{5.12}$$

where $log\sigma_{mt}$ is log-market-volatility, $R_{mt}$is market return and R^F_{mt} is foreign market return at time t.

The final stage is to examine herding concerned with fundamental market and macroeconomic factors by further adding macroeconomics factors of Term Spread (TS) and the relative Treasury Bill rate (RTB) in the measurement equation of the state space model 2. It examines whether such factors are the causes of the deviation of the funds' betas. The estimation model becomes the model 3:

$$log[Std_c(\beta^b_{imt})] = \mu_m + H_{mt} + \theta_{m1} log\sigma_{mt} + \theta_{m2} R_{mt} + \theta_{m3} R^F_{mt}$$

$$+\theta_{m4} TS_t + \theta_{m5} RTB_t + v_{mt} \qquad (5.13)$$

$$H_{mt} = \phi_m H_{mt-1} + \eta_{mt} \qquad (5.14)$$

where TS_t is the term spread at time t. It is the difference between the UK 3-month Treasury Bill rate and the UK 10-year Government Bond rate. RTB is the relative treasury bill rate. It is the difference between the UK 3-month Treasury Bill rate and its 4-week moving average for weekly interval (12-month moving average for monthly data). The estimated results from open-ended and closed-end funds are presented in Table 5.15.

The estimations from open-ended and closed-end funds reveal very similar features. Among the weekly herding estimations, the results in the first column show that the estimated ϕ_m is large and statistically significant at the 1% level, indicating that herding is highly persistent in the market. $|\phi_m| \leq 1$ satisfies the requirement that herding toward the market portfolio is not an explosive process, hence H_{mt} is stationary. The estimated weekly $\sigma^2_{m\eta}$ has a significant probability value less than the 10% significant level. This indicates that the standard deviation of η_{mt} is highly possibly not zero, implying $H_{mt} \neq 0$. This can be interpreted as the existence of herding. The significant of ϕ_m also supports the particular autoregressive structure.

The results in the second column show that after including fundamental market factors, $\sigma^2_{m\eta}$ is still significant at the 10% level, proving the evidence of herding after adding the three market fundamental variables. The large and significant ϕ_m, again, states the highly persistent herd behaviour. Market return is significant at the 10% level in open-ended funds, implying that the domestic equity market returns have some explanatory power to open-ended funds' $Std_c(\beta^b_{imt})$, but the significant $\sigma^2_{m\eta}$ indicates that market returns do not generate much investor herding behaviour.

The third column shows that $\sigma^2_{m\eta}$ and ϕ_m do not change much after taking market fundamental and macroeconomic factors into account, indicating that market fundamental and macroeconomic factors do not vary the Beta dispersion much. The significance of some of the factors demonstrates their explanatory power to the $Std_c(\beta_{imt}^b)$. However, the still significant $\sigma_{m\eta}^2$ in model 3 indicates that the fundamental and macroeconomic factors do not generate much investor herding behaviour.

Estimates form monthly data suggest very similar pictures to those of weekly data. $\phi_m$is large and significant and $\sigma_{m\eta}^2$ has a significant probability value more than 5% but less than 10%, again, suggesting that $H_{mt} \neq 0$ for all t. This can be interpreted as evidence for the existence of highly persistent herding. In model 2 and 3, the significant coefficient of market volatility (θ_{m1}) and/or foreign market return (θ_{m3}) state that they are the factors to explain the changes in the $Std_c(\beta_{imt}^b)$ but they cannot take over the explanatory power of the herding variable, H_{mt}.

Table 5.15: Estimates of state-space basic models for herding in the UK mutual funds

Table 5.15 reports the results of regressions of the following general form:

Model 1: $\log[\mathrm{Std}_c(\beta^b_{mt})] = \mu_m + H_{mt} + \upsilon_{mt}$ and $H_{mt} = \emptyset_m H_{mt-1} + \eta_{mt}$

Model 2: $\log[\mathrm{Std}_c(\beta^b_{mt})] = \mu_m + H_{mt} + \theta_{m1}\log\sigma_{mt} + \theta_{m2}R_{mt} + \theta_{m3}R^F_{mt} + \upsilon_{mt}$ and $H_{mt} = \emptyset_m H_{mt-1} + \eta_{mt}$

Model 3: $\log[\mathrm{Std}_c(\beta^b_{mt})] = \mu_m + H_{mt} + \theta_{m1}\log\sigma_{mt} + \theta_{m2}R_{mt} + \theta_{m3}R^F_{mt} + \theta_{m4}TS_t + \theta_{m5}RTB_t + \upsilon_{mt}$ and $H_{mt} = \emptyset_m H_{mt-1} + \eta_{mt}$

where$\mathrm{Std}_c(\beta^b_{imt})$ represent the standard deviation of UK fund betas, H_{mt} is the unobservable herding parameter; $\log\sigma_{mt}$ is log-market-volatility, $R_{mt}$is market return and R^F_{mt} is foreign market return at time t; TS_t is the term spread at time t. It is the difference between the UK 3-month Treasury Bill rate and the UK 10-year Government Bond rate. RTBis the relative treasury bill rate. It is the difference between the UK 3-month Treasury Bill rate and its 4-week moving average for weekly interval (12-month moving average for monthly data).
The sample period is January 1996 – June 2010. Standard Deviations are given in parentheses. ***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

	Open-ended Funds						Closed-end Funds					
	Cross-sectional variance of weekly betas			Cross-sectional variance of monthly betas			Cross-sectional variance of weekly betas			Cross-sectional variance of monthly betas		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
μ_m	-0.987432*** (0.078410)	-0.986901*** (0.079246)	-0.985873*** (0.079100)	-1.392156*** (0.112171)	-1.416285*** (0.118011)	-1.41371*** (0.124758)	-0.611866 *** (0.0324986)	-0.612351*** (0.031832)	-0.610914*** (0.029683)	-1.010265*** (0.019915)	-1.019149*** (0.020430)	-1.020053*** (0.020974)
ϕ_m	0.990471*** (0.007759)	0.990753*** (0.007665)	0.99117*** (0.007637)	0.989348*** (0.013857)	0.989397*** (0.013672)	0.991308*** (0.011850)	0.960937*** (0.0237995)	0.964495*** (0.022327)	0.956425*** (0.027643)	0.784138*** (0.121990)	0.766854*** (0.128472)	0.778514*** (0.119173)
θ_{m1}		-0.000146 (0.012079)	-0.000292 (0.012066)		0.003227*** (0.011622)	0.0332084*** (0.011662)		-0.009006 (0.011344)	-0.007470 (0.011370)		0.010920 (0.007965)	0.010389 (0.008013)
θ_{m2}		0.013246* (0.007973)	0.014838* (0.008055)		-0.004404 (0.006256)	-0.002990 (0.006376)		0.000849 (0.007384)	0.010299 (0.007477)		-0.004475 (0.004307)	-0.005094 (0.004375)
θ_{m3}		-0.008564 (0.007684)	-0.006944 (0.007749)		0.011904** (0.005639)	0.010351* (0.005855)		-0.005900 (0.007105)	-0.006286 (0.007200)		0.006841* (0.003883)	0.007486* (0.004002)
θ_{m4}			-0.006627 (0.004700)			-0.002475 (0.002742)			-0.006930 (0.005203)			0.001397 (0.001962)
θ_{m5}			-0.010870** (0.005515)			0.000118 (0.002603)			-0.007690* (0.004481)			0.000105 (0.002004)
σ^2_{mv}	0.122963** (0.006452)	0.122632*** (0.006442)	0.122486*** (0.006425)	0.043245*** (0.004716)	0.039581*** (0.004350)	0.039826*** (0.004364)	0.105723*** (0.005906)	0.105549*** (0.005812)	0.104574*** (0.005913)	0.016891*** (0.002780)	0.015886*** (0.002853)	0.015989*** (0.002762)
$\sigma^2_{m\eta}$	0.000529* (0.000335)	0.000511* (0.000332)	0.000465* (0.000312)	0.000497* (0.000360)	0.000548* (0.000384)	0.0004576* (0.000329)	0.001192* (0.00085)	0.000943* (0.000702)	0.001194* (0.000921)	0.002715* (0.002048)	0.003116* (0.002320)	0.002988* (0.002141)

5.6.2. CAPM betas estimated by Kalman Filter method

In their approach, Hwang & Salmon (2004) estimate the standard OLS using non-over lapping monthly betas. This may lead to estimation error in the cross-sectional standard deviation of the betas. They suggest that the presence of estimation error makes it more difficult to find significant estimates of ϕ, though it does not affect the estimated herding parameter. They further point out that more significant values of ϕ can be found if the interval over which the initial beta estimates are computed is lengthened. However, lengthening the interval would reduce the ability to capture more rapid movements in herding. Moreover, the HS approach is based on the argument that investor sentiment such as herding may lead to time-varying betas. Black, Fraser and Power (1992) suggest that the OLS regression model will be inefficient if the betas are time-varying and therefore it may be an unsuitable procedure for estimating the time varying betas. They propose instead to use the Kalman Filter to obtain the parameters. This procedure allows a set of 'hyper-parameters' to be obtained. It enables daily betas to be obtained as well as weekly and monthly betas. In this section, the betas are recalculated by applying by Black et al (1992) method and the herding measure is estimated by utilising the models presented in the previous section. Table 5.16A and Table 5.16B reports the regression results open-ended and closed-end funds respectively.

In the daily interval, the estimated parameters are very similar between open-ended and closed-end funds. Under the basic model, the results (in the 1st column) show that the estimated ϕ_m is again large and highly significant, indicating that herding is highly persistent in the market. The estimated daily $\sigma^2_{m\eta}$ is significant at the 1% level, meaning that the standard deviation of η_{mt} is statistically non-zero. This shows evidence of herding towards the market portfolio. Estimates of model 2 (column 2) show that returns of foreign market, θ_{m3}, is significant, demonstrating that it has some explanatory power to the changes in the $Std_c(\beta^b_{imt})$. The significance of $\sigma^2_{m\eta}$, however, suggests that herding still exists, and the significant of ϕ_m indicates the herding is still highly persistent. This implies that the institutional investor herding behaviour is not caused by market fundamentals but other factors such as investor sentiment.[40]

[40]The macroeconomic variables are not available in daily frequency. Model 3 cannot be estimated.

In the weekly interval, the results from open-ended and closed-end funds are very similar again. $\sigma_{m\eta}^2$ is highly significant, demonstrating $H_{mt} \neq 0$ for all t . This provides evidence for the existence of herding. ϕ_m is highly significant suggesting that herding is highly persistent among the investment portfolios. The significant level of $\sigma_{m\eta}^2$ does not change much from model 1 (the basic model) to model 3 which includes market fundamental and macroeconomic factors. This suggests that the herding behaviour is not caused by the market fundamental and macroeconomic factors. Although some of the factors have explanatory power to the changes of the standard deviation of betas, the still significant ϕ_m and $\sigma_{m\eta}^2$ suggests that they do not generate much herding activity.

Similar to the weekly result, estimated $\sigma_{m\eta}^2$ and ϕ_m from monthly data are significant, suggesting a persistent herding behaviour. Although several market and macroeconomic fundamental coefficients are significant demonstrating some explanatory power to the changes in the $Std_c(\beta_{imt}^b)$. However, $\sigma_{m\eta}^2$ is significant, demonstrating that the fundamentals and macroeconomic factors do not generate much herding, and the high value of ϕ_m implies that herding behaviour still highly persistent. This suggests that the herding behaviour detected in model 1 is not caused by market and macroeconomic fundamentals. Instead, it again may be caused by investor sentiment.

It is worth noting that in the monthly estimation, there is a different significant level of $\sigma_{m\eta}^2$ from open-ended funds to closed-end funds. The $\sigma_{m\eta}^2$ of open-ended funds has much higher significance level than that of closed-end funds, indicating that managers of open-ended funds are more likely to herd to a greater level than those of closed-end funds. This may be explained by the structure of the open-ended. As open-ended funds can issue shares or have to redeem investment any time when investors require, fund managers have the pressure to keep investment portfolios at the similar risk level to their peers' to justify their investment returns. This leads to the portfolio betas diverting from the fundamental beta expected by the rational asset model.

The estimated result from OLS Betas and Kalman Filter Betas both suggest herding evidence of UK fund managers, and the herding behaviour of fund managers is persistent. In comparing the estimation results, coefficients from the Kalman Filter betas exhibit much stronger herding signs than that from the OLS betas. In all three models, the parameters, standard deviation of the herding variable has greater value in herding estimation from the Kalman Filter betas, and the significant level of standard deviation of the herding by Kalman Filter beta is also greater than that in OLS beta herding estimations. This can be because the Kalman Filter method is more efficient in estimating time-varying Betas (Black, Fraser and Power, 1992) which contain better information.

5.7 Conclusion

In this chapter institutional investor herding is investigated by applying the measures of return and CAPM beta dispersion of UK open-ended funds and UK closed-end funds. The sample open-ended funds are equity focused mutual funds and the closed-end funds are randomly chosen from those listed on London Stock Exchange, where investment focuses can vary. The investigation is conducted by applying daily, weekly and monthly data to study fund managers herd behaviour in different investment intervals.

The rationale is that a rise in herding would be reflected in a decrease in dispersion of fund returns or betas. Instead of investigating whether fund managers are crowded into or out of one or a group of stocks by examining micro-level of account data, the analysis utilises returns of funds as an indicator to explore the style of portfolio that fund managers follow to each other, i.e. the dispersion of fund returns decreases if fund managers herd on the return of a benchmark portfolio return.

Applying CH approach, institutional herding behaviour in market extreme times was examined but no evidence have been found. Introducing financial crisis to define market stress periods, the study finds evidence of fund managers herding in the short and medium investment intervals during the pre-crisis bubble building period. This may be because when the market is overvalued by some irrational agents, fund managers ride the bubble to maximise their profit and to avoid losing out to their peers. In the long term interval there is no clear sign of herd behaviour of fund managers, but the significant larger return dispersion in the crisis period suggests the possibility of herding in the pre-crisis and normal periods. This may indicate that investors herd in normal time. It may confirm the statement that financial crisis is a process of asset prices correcting to the fundamentals from the bubble.

Fund manager herd behaviour was further investigated by using CCK method which examines the relation between cross-section return dispersion and absolute market return. The estimated coefficients provide no significant evidence of herding behaviour among fund managers. Different market conditions including the up- and down-market conditions, up- and down-trading-volume, up- and down-foreign-market-return and high- and low-volatility market conditions were also considered to examine herding behaviour in different markets and the possible asymmetric effect of herding behaviour. Estimated results do not provided significant evidence of herding behaviour, and there is a general indication of symmetric return dispersion in the market.

While CH and CCK approaches investigate herding behaviour based on the assumption that investors herd (or herd in a greater degree) in certain periods (or under certain conditions), HS focuses on examining what factors investors herd upon. HS suggest that herd behaviour is more likely to be persistent and affects CAPM betas of portfolios. Therefore, CAPM betas dispersions of UK open-ended and closed-end funds are examined for studying institutional herd behaviour. It appears that there is strong evidence of herding among fund managers in the risk-return relation of their portfolio returns and the market return. The study also demonstrates that the herd behaviour is not caused by market fundamental and macroeconomic factors, instead, it perhaps arises from investor sentiment.

In the study, CAPM beta was obtained by using OLS and Kalman Filter technique respectively. The estimated parameters from OLS betas address similar results to those from Kalman Filter betas, however the level of significance of herding evidence was greater in the Kalman Filter betas than that of OLS betas. The Kalman Filter technique also overcomes the OLS method issue of only relatively lower frequency betas being obtained by estimating higher frequency returns. It allows daily fund betas to be used for herding study in addition to weekly and monthly betas. The estimated herding parameters provides stronger evidence of fund manager herd behaviour in all three investment intervals (daily, weekly and monthly), and the factors which causes managers herding is more likely to be investor sentiment rather than market fundamental and macroeconomic elements.

In the examination of UK institutional herding behaviour, the results from UK open-ended funds are very similar to those from closed-end funds. Although they are in a different form of structure and have very different investment focuses, the examination of return dispersions by using CH and CCK approach suggest no significant evidence of herding behaviour of the fund managers and the examination of CAPM betas by HS approach indicate significant herding behaviour fund managers. This demonstrates that fund managers are more likely to herd on the systematic risk of the market rather than in a specific period or condition. This may also imply that herding behaviour is a general practice among the fund managers.

Table 5.16A: Estimates of state-space models for herding in the UK open-ended funds by using Kalman Filter betas

Table 5.16A reports the results of regressions of the following general form:

Model 1: $\log[\mathrm{Std}_c(\beta^b_{mt})] = \mu_m + H_{mt} + \upsilon_{mt}$ and $H_{mt} = \emptyset_m H_{mt-1} + \eta_{mt}$

Model 2: $\log[\mathrm{Std}_c(\beta^b_{mt})] = \mu_m + H_{mt} + \theta_{m1}\log\sigma_{mt} + \theta_{m2}R_{mt} + \theta_{m3}R^F_{mt} + \upsilon_{mt}$ and $H_{mt} = \emptyset_m H_{mt-1} + \eta_{mt}$

Model 3: $\log[\mathrm{Std}_c(\beta^b_{mt})] = \mu_m + H_{mt} + \theta_{m1}\log\sigma_{mt} + \theta_{m2}R_{mt} + \theta_{m3}R^F_{mt} + \theta_{m4}TS_t + \theta_{m5}RTB_t + \upsilon_{mt}$ and $H_{mt} = \emptyset_m H_{mt-1} + \eta_{mt}$

where $\mathrm{Std}_c(\beta^b_{imt})$ represent the standard deviation of UK fund betas, H_{mt} is the unobservable herding parameter; $\log\sigma_{mt}$ is log-market-volatility, R_{mt} is market return and R^F_{mt} is foreign market return at time t; TS_t is the term spread at time t. It is the difference between the UK 3-month Treasury Bill rate and the UK 10-year Government Bond rate. RTBis the relative treasury bill rate. It is the difference between the UK 3-month Treasury Bill rate and its 4-week moving average for weekly interval (12-month moving average for monthly data).
The macroeconomic variables are not available in daily frequency. Therefore, the model 3 cannot be estimated. The sample period is January 1996 – June 2010. Standard Deviations are given in parentheses. ***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

Coefficients	Cross-sectional variance of daily betas		Cross-sectional variance of weekly betas (83 funds)			Cross-sectional variance of monthly betas		
	Model 1	Model 2	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
μ_m	-1.493539*** (0.030479)	-1.493243*** (0.030574)	-1.583567** (0.672617)	-1.579118** (0.682150)	-1.576918** (0.682605)	-1.802604*** (0.666231)	-1.791269** (0.691002)	-1.792034** (0.693212)
ϕ_m	0.980917*** (0.003777)	0.980995*** (0.003772)	0.998503*** (0.001871)	0.998560*** (0.001806)	0.998570** (0.001794)	0.991952*** (0.009417)	0.992538*** (0.008843)	0.992621*** (0.008767)
θ_{m1}		0.000258 (0.000382)		0.001463 (0.001074)	0.001569 (0.001070)		0.005473 (0.004212)	0.005135 (0.004218)
θ_{m2}		-0.000402 (0.000372)		-0.002547*** (0.000665)	-0.002323*** (0.000670)		0.003563* (0.002130)	0.003287 (0.002143)
θ_{m3}		-0.000661** (0.000337)		0.001324** (0.000646)	0.001249* (0.000647)		-0.003890** (0.001965)	-0.003540* (0.001981)
θ_{m4}					-0.000778* (0.000426)			0.000197 (0.001141)
θ_{m5}					0.000082 (0.000504)			-0.001265 (0.001344)
σ^2_{mv}	-	-	-	-	-	-	-	-
$\sigma^2_{m\eta}$	0.001342*** (0.000030)	0.001340*** (0.000030)	0.002052*** (0.000102)	0.002008*** (0.000100)	0.001990*** (0.000099)	0.011680*** (0.001217)	0.011324*** (0.001180)	0.011230*** (0.001170)

Table 5.16B: Estimates of state-space models for herding in the UK Closed-end funds by using Kalman Filter betas

Table 5.16B reports the results of regressions of the following general form:

Model 1: $\log[\mathrm{Std}_c(\beta^b_{mt})] = \mu_m + H_{mt} + \upsilon_{mt}$ and $H_{mt} = \emptyset_m H_{mt-1} + \eta_{mt}$

Model 2: $\log[\mathrm{Std}_c(\beta^b_{mt})] = \mu_m + H_{mt} + \theta_{m1}\log\sigma_{mt} + \theta_{m2}R_{mt} + \theta_{m3}R^F_{mt} + \upsilon_{mt}$ and $H_{mt} = \emptyset_m H_{mt-1} + \eta_{mt}$

Model 3: $\log[\mathrm{Std}_c(\beta^b_{mt})] = \mu_m + H_{mt} + \theta_{m1}\log\sigma_{mt} + \theta_{m2}R_{mt} + \theta_{m3}R^F_{mt} + \theta_{m4}TS_t + \theta_{m5}RTB_t + \upsilon_{mt}$ and $H_{mt} = \emptyset_m H_{mt-1} + \eta_{mt}$

where$\mathrm{Std}_c(\beta^b_{imt})$ represent the standard deviation of UK fund betas, H_{mt} is the unobservable herding parameter; $\log\sigma_{mt}$ is log-market-volatility, $R_{mt}$is market return and R^F_{mt} is foreign market return at time t; TS_t is the term spread at time t. It is the difference between the UK 3-month Treasury Bill rate and the UK 10-year Government Bond rate. RTBis the relative treasury bill rate. It is the difference between the UK 3-month Treasury Bill rate and its 4-week moving average for weekly interval (12-month moving average for monthly data).
The macroeconomic variables are not available in daily frequency. Therefore, the model 3 cannot be estimated. The sample period is January 1996 – June 2010. Standard Deviations are given in parentheses.

***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

Coefficients	Cross-sectional variance of daily betas		Cross-sectional variance of weekly betas			Cross-sectional variance of monthly betas		
	Model 1	Model 2	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
μ_m	-1.43049 (1.181365)	-1.421931 (1.182523)	-0.646538*** (0.018991)	-0.644569*** (0.018512)	-0.648129*** (0.018747)	-0.196591** (0.080966)	-0.158018** (0.074414)	-0.176577** (0.079228)
ϕ_m	0.999649*** (0.000414)	0.999651*** (0.000411)	0.674711*** (0.070466)	0.662586*** (0.072842)	0.692625*** (0.072501)	0.902846*** (0.065543)	0.907973*** (0.068907)	0.925452*** (0.053068)
θ_{m1}		0.000567 (0.000382)		-0.021046*** (0.007302)	-0.021704*** (0.007223)		-0.066031*** (0.020276)	-0.069963*** (0.019716)
θ_{m2}		-0.000228 (0.000372)		0.003771 (0.004718)	0.002530 (0.004708)		0.008537 (0.010784)	0.007929 (0.010632)
θ_{m3}		-0.001016*** (0.000337)		-0.003067 (0.004522)	-0.000707 (0.004536)		0.000811 (0.009731)	-0.000778 (0.009782)
θ_{m4}					-0.002618 (0.003454)			0.007166 (0.004716)
θ_{m5}					-0.000109 (0.002884)			0.007422 (0.004829)
σ^2_{mv}	-	-	0.021814* (0.006341)	0.020979*** (0.006539)	0.023001*** (0.006059)	0.112986*** (0.016244)	0.109824*** (0.015375)	0.105345*** (0.004889)
$\sigma^2_{m\eta}$	0.001369*** (0.000031)	0.001364*** (0.000030)	0.028652*** (0.006341)	0.029207*** (0.008418)	0.024681*** (0.007663)	0.011166* (0.008228)	0.008114 (0.006941)	0.006312* (0.004889)

Chapter 6 Institutional herd behaviour and investor sentiment

6.1 Introduction

The experimental evidence in social psychology suggests that individuals tend to abide by the group decision even when they perceive the group to be wrong. Investors, much like every human being, dwell in societies among other people with whom they interact. Herd behaviour in financial markets is believed to reflect the irrational response rather than the outcome of rational decision making based on asset fundamental. The price of securities is affected by the interactions of trading activities of investors who hold heterogeneous beliefs, preferences, and trading strategies. The unpredictable nature of noise traders' sentiment generates a new source of risk preventing rational traders from correcting mispricing, instead, rational traders may join 'the crowds' by taking a ride. Bikhchandani and Sharma (2001) divide herd behaviours into rational and irrational and define irrational herding as intentional herd behaviour caused by investor's sentiment.

Hwang and Salmon (2007) propose a model which incorporates the interaction between sentiment and herding to show that herding activity increases with market-wide sentiment. They show that individual asset returns are expected to increase regardless of their systematic risks when market-wide sentiment is positive, hence increasing herding. Their empirical results show that investor sentiment explains up to 25 percent of beta herding. However, the model is based on examining how investor sentiment biasesthe betas of individual securities. Herding can also be the behaviour of returns of individual assets matching with the returns of the market as suggested by CH and CCK. A more direct method therefore, is used to examine the relation between investor sentiment and herd behaviour in this chapter.

6.2 Weekly UK institutional herding and investor sentiment

As discussed in the previous chapters, theoretically, institutional investors' herd behaviour can be caused by information, agency problem, and/or investor sentiment. In order to investigate the causal relation from investor sentiment to institutional herding, regressions are conducted upon the herding measures and the sentiment indexes. The herding measures include Cross-sectional absolute deviation (CSAD), Cross-sectional standard deviation (CSSD) and the estimated herd measurement by using HS method, named HSH. In chapter 5, the state space model (equation 4.10 and 4.11)[41] is used for detecting the institutional herding behaviour. The unobservable herding variable, H_{mt}, can therefore be estimated using the log standard deviation of open-ended funds as HSH_{op} and log standard deviation of closed-ended funds as HSH_{cl}.

The investor sentiment measures include the two composed UK investor sentiment indexes: the UK market investor sentiment index, $SENT$, and the UK institutional investor sentiment index,$SENT^{p}$. Foreign investor sentiment is also considered in the analysis and represented by the US investor sentiment. The two US survey indices, AAII and II, are used to examine the influence from US individual sentiment and institutional sentiment respectively on UK institutional herding. The highest frequency of investor sentiment indices for UK investor sentiment constructed in Chapter 3 is in weekly. Investigations of whether institutional herding is affected by investor sentiment are therefore firstly conducted using weekly data.

Table 6.1 presents the statistical summary of the variables. The autocorrelation tests show that all the variables are auto-correlated, especially the herding measure HSH. The first order autocorrelation coefficient is 0.989, which is very close to unity. The Augmented Dickey-Fuller (ADF) test of unit root shows that HSH_{op}cannot reject the null hypothesis of unit root, demonstrating the non-stationary nature of the series. Therefore, the first difference of HSH_{op}, $DHSH_{op}$, is considered and the ADF test indicates that the null of unit root is rejected at the 1% significance level. The autocorrelation coefficient also suggests that the series is unlikely to be autocorrelated.

In order to explore the relationship between UK institutional herding and investor sentiment, tests of correlations between institutional herding measures and investor sentiment indexes are conducted: the correlation coefficients are reported in Table 6.2

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[41] $log[Std_c(\beta^b_{imt})] = \mu_m + H_{mt} + v_{mt}$, H_{mt}=$\phi_m H_{mt-1} + \eta_{mt}$ where $Std_c(\beta^b_{imt})$ represent the standard deviation of UK fund betas, H_{mt} is the unobservable herding parameter.

Panel A. The negative coefficients of $CSAD$and $CSSD$, and the positive coefficients of HSH suggest a positive correlation between investor sentiment and institutional herd behaviour regardless of whether they are open-ended or closed-end funds. Absolute terms of the coefficients between return dispersions and $SENT^p$ are higher than that of $SENT$ for both category funds. For instance, the correlation between $CSAD_{op}$ and $SENT^p$ is 47% in absolute terms compared to 35% between $CSAD_{op}$and $SENT$.This suggests that institutional herding is more likely to have a stronger correlation to institutional sentiment than to individual sentiment. However, the correlation coefficients cannot prove that the stronger correlation to institutional sentiment is significant. This will be subject to further examination in the following sections. For the HSH measures, however, there is a different feature between open-ended funds and closed-end funds. The open-ended funds' coefficients indicate that the herd measure may have a higher level of correlation to UK market sentiment than to UK institutional sentiment, and herding of close-ended funds has higher level of correlation to the UK institutional sentiment.

The correlations between the UK institutional herd behaviour and US investor sentiment are also examined and the results are shown in Table 6.2 Panel A. The coefficients are all statistically significant at the 1% level, demonstrating that both US individual sentiment and US institutional sentiment are correlated to the UK institutional herd behaviour. Moreover, comparing the absolute value of the coefficients, it appears that the UK institutional herding may have a stronger correlation with the US institutional sentiment than with US individual sentiment. In addition, UK institutional herding generally has a stronger correlation to UK investor sentiment than to that of US investor sentiment. However, these are only indications from values of coefficients; they will still be subjected to further significant examination.

Granger-causality tests whether institutional herding is led by investor sentiment or vice versa are presented in Table 6.2 Panel B. Both open-ended and closed-end funds reveal very similar pictures. When herding is measured by CSAD and CSSD, the p-values show that the null of Granger-noncausality from UK market investors sentiment to herding cannot be rejected at the 5% level, and the null of Granger-noncausality from herding to investor sentiment are rejected at the 1% significance level. This suggests that UK market sentiment is led by UK institutional herding. For the UK institutional sentiment, p-values give no clear sign of which one is the leading factor since both direction of Granger-noncausality assumption are rejected at the 5% significance level.

When UK institutional herding is measured by HSH, both null hypotheses are rejected at the 1% level, giving no clear signal of whether herding leads to UK market sentiment or vice versa. However, p-values hint that it is more likely that UK market sentiment leads to UK institutional herding. This corresponds with that which HS suggested: that investor's sentiment causes the diversion of CAPM beta from their fundamentals to market average. The examination of UK institutional herding in section 5.6 also indicated that UK institutional herding is not caused by market fundamental and macroeconomic factors, instead, it may be caused by investor sentiment. For UK institutional sentiment, the p-values indicate that UK institutional sentiment is led by institutional herding but not vice versa.

For the US investor sentiment measures, the US individual sentiment statistically and significantly Granger-causes the UK institutional herding at the 5% level, but not vice versa. The US institutional sentiment does not show signs that it leads to or is led by the UK institutional herd behaviour when using CASD or CSSD to measure herd behaviour. However, the p-values indicate that there is a high probability that US institutional sentiment leads to UK institutional herding. The test results by using HSH as the herding measure confirms the suggestion.

Table 6.1: Statistic summary of weekly herding and sentiment variable

AAII is American Association of Individual Investors index; GMI is German Market Indicator; II is Investors Intelligence index; SENT isUK market investor sentiment index; $SENT^p$is UK institutional investor sentiment; $CSAD_{op}$ is Cross Section Absolute Deviation of UK open-ended funds; $CSSD_{op}$ is Cross Section Standard Deviation of UK open-ended funds; HSH_{op} is the herding measure generated by Hwang and Salmon (2004) approach from UK open-ended funds; $DHSH_{op}$ is the first order of HSH_{op}; $CSAD_{cl}$ is Cross Section Absolute Deviation of UK closed-end funds; $CSSD_{cl}$ is Cross Section Standard Deviation of UK closed0end funds; HSH_{cl} is the herding measure generated by Hwang and Salmon (2004) approach from UK closed-end funds.The data cover the period 1st January 1996 to 30th June 2011.
AC (1) is autocorrelation coefficient at one lag. **AC (2)** is autocorrelation coefficient at 2 lags. **ADF** is Augmented Dickey-Fuller test statistic with maximum 52 lags for weekly indexes and 12 lags for monthly indexes. **Obs** is number of observation. ***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

Variable	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Sum Sq. Dev.	AC (1)	AC (2)	ADF	Obs
AAII	0.1092	0.1933	-0.0893	2.7079	3.942019	30.1047	0.672	0.567	-9.2572***	807
II	0.1863	0.1353	-0.7417	3.5538	84.51907***	14.7866	0.939	0.859	-5.9866***	809
SENT	50.1432	26.1439	-0.4746	1.8324	76.1325***	550904.3	0.872	0.733	-7.954***	807
$SENT^p$	0.9436	0.5187	-0.8072	5.2046	251.3766***	217.1586	0.708	0.686	-4.9581***	808
$CSAD_{op}$	0.8963	0.5799	2.3976	11.6998	3318.170***	271.043	0.488	0.363	-8.3242***	807
$CSSD_{op}$	1.1197	0.6453	2.3081	11.58805	3196.536***	335.5822	0.519	0.410	-7.8868***	807
HSH_{op}	-0.0058	0.1383	0.0980	2.7565	3.2900	15.4453	0.989	0.977	-2.0198	808
$DHSH_{op}$	-0.0001	0.0203	0.4774	4.6429	68.7410***	0.3309	0.027	0.038	-27.7645***	807
$CSAD_{cl}$	1.4210	0.7477	2.5860	15.3109	6002.99***	451.1929	0.506	0.453	-5.7849***	808
$CSSD_{cl}$	1.9782	0.9911	2.3195	12.5475	3793.38***	792.6433	0.527	0.460	-4.0997***	808
HSH_{cl}	0.0022	0.0853	-0.0571	2.3633	14.0700***	5.8623	0.960	0.918	-3.9679***	807

Table 6.2: Weekly correlation and Granger Causality tests: institutional herding measures and investor sentiment

SENT isUK market investor sentiment index; $SENT^p$is UK institutional investor sentiment; $CSAD_{op}$ is Cross Section Absolute Deviation of UK open-ended funds; $CSSD_{op}$ is Cross Section Standard Deviation of UK open-ended funds; HSH_{op} is the herding measure generated by Hwang and Salmon (2004) approach from UK open-ended funds; $DHSH_{op}$ is the first order of HSH_{op}; $CSAD_{cl}$ is Cross Section Absolute Deviation of UK closed-end funds; $CSSD_{cl}$ is Cross Section Standard Deviation of UK closed0end funds; HSH_{cl} is the herding measure generated by Hwang and Salmon (2004) approach from UK closed-end funds. AAII is American Association of Individual Investors index; II is Investors Intelligence index. The data cover the period 1st January 1996 to 30th June 2011.

Test 1: H_0: Granger-noncausality from herding measures to the sentiment indexes.
Test 2: H_0: Granger-noncausality from sentiment indexes to herding measures.

The tabulated statistics are the p-valus of the test statistics with 5 lags.
***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

Panel A: Correlation tests

	Open-ended funds			Closed-end funds		
	$CSAD_{op}$	$CSSD_{op}$	$DHSH_{op}$	$CSAD_{cl}$	$CSSD_{cl}$	HSH_{cl}
Variable	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
AAII	-0.2595***	-0.2373***	0.1249***	-0.1897***	-0.1575***	0.2228***
II	-0.3803***	-0.3949***	0.1439***	-0.3743***	-0.3660***	0.2509***
SENT	-0.3453***	-0.3607***	0.1772***	-0.3689***	-0.3566***	0.2586***
$SENT^p$	-0.4730***	-0.5111***	0.0891**	-0.5257***	-0.4994***	0.4713***

Panel B: Granger Causality test

	$CSAD_{op}$		$CSSD_{op}$		$DHSH_{op}$		$CSAD_{cl}$		$CSSD_{cl}$		HSH_{cl}	
	Test 1	Test 2	Test 1	Test 2	Test 1	Test 2	Test 1	Test 2	Test 1	Test 2	Test 1	Test 2
AAII	0.6778	0.0105	0.7551	0.0079	0.9485	0.0071	0.3877	0.0019	0.6434	0.0079	0.9983	0.0004
II	0.0079	0.0008	0.0022	0.0006	0.8019	0.0001	0.0077	0.0005	0.0535	0.0021	0.9829	0.0007
SENT	0.0001	0.0782	0.0004	0.1029	0.0006	0.0003	0.0003	0.1420	0.0006	0.2295	0.0044	0.0002
$SENT^p$	<0.0001	0.0022	<0.0001	0.0022	0.0147	0.2408	<0.0001	0.0003	<0.0001	0.0037	0.0334	0.0937

6.2.1. UK institutional herding and UK investor sentiment

In the empirical studies in Chapter 5, it is suggested that the fund managers' portfolio herding is likely to be caused by investor sentiment. Thus, a regression of herding measure on the sentiment indexes can provide more details of investor sentiment causing herd behaviour. The analysis starts by only looking at the UK investor sentiment effect on the UK institutional herd behaviour by using weekly data. The model to be estimated is started by including 5 lags of sentiment terms in the regression with lagged control variables:

$$H_t = \alpha_0 + \sum_{j=1}^{5} \alpha_j H_{t-j} + \sum_{i=0}^{5} \beta_i SENT_{t-i} + \sum_{i=0}^{5} \gamma_i SENT_{t-i}^{p} + \varepsilon_t \qquad (6.1)$$

whereH_t is the level of investor's herding behavior at time t, and it is measured by $CSAD$, $CSSD$, or HSH $(or\ DHSH)$. The estimated coefficients of some high order lagged terms variables are statistically insignificant at the 10% level in the CSAD and CSSD regressions. Therefore, the above models are amended to be Model 2 by dropping the insignificant lagged terms of variable.

The estimated results of open-ended funds are reported in Table 6.3A. When UK institutional herding is measured by cross-section return dispersions, CSAD or CSSD, the estimated coefficients demonstrate that both UK market sentiment and UK institutional sentiment have some impact on UK institutional herding behaviour. The negative coefficients of $SENT_t$ and $SENT_t^p$ indicates that higher investor sentiment leads to a lower level cross-section return dispersion, meaning the degree of herd behaviour is high. The positive value of $SENT_{t-1}$ implies a reverse effect of the last period of market sentiment on institutional herd behaviour which corresponds to the reverse effect of investor sentiment in Chapter 3. If the immediate impact of investor sentiment changes is to induce herding behaviour, then herd reversals in the subsequent week(s), increasing UK institutional investors changing the degree of herding behaviour as a result. However, the reverse effect does not appear in the institutional sentiment, which suggests that institutional sentiment effect on herding behaviour is more likely persistent in the same direction. This can be explained by institutional investors normally being more confident in their investment decision making than individual investors, and they are more likely to stick with their investment strategies. The significance of higher order lagged term coefficients of $SENT_{t-4}$ and $SENT_{t-3}^{p}$ also indicates that UK investor sentiment has a relatively long run effect on UK institutional herd behaviour.

When herding is measured by HSH_{op}, $SENT_t$ and $SENT_t^p$ are significant, again, showing that current UK market and institutional sentiment have influence over UK institutional herding. Positive values of the coefficients state that high investor sentiment leads to high level of UK institutional herd behaviour. The significance of higher order of lagged term of sentiment coefficient, $SENT_{t-5}$ and $SENT_{t-5}^{p}$, also suggests that UK investor sentiment has a relatively long influence over institutional investor herd behaviour. This agrees with the results from the CSAD measure, which may indicate that CSAD and HSH are better measures of institutional herding.

The estimated results of closed-end funds (Table 6.3B) present very similar features as those of open-ended funds. UK market sentiment and institutional sentiment both have an effect on UK institutional herding behaviour. The reverse effect of market sentiment appears when herding is measured by return dispersions. However, the long-term impact on herding of open-ended fund managers does not appear on herding of closed-end fund managers, which suggests that investor sentiment effect on institutional herding may be over a relatively short term. The long-term effect in the open-end fund herding may come from the individual investors' sentiment impact on open-end fund managers, as the investment performances are constantly assessed by individual investors who are more likely the noise traders.

The regression results from both category UK mutual funds demonstrate that the institutional herd behaviour, which is measured by the return or beta dispersion of mutual funds in the UK market, to some degree, is a result of UK investor sentiment. This suggests that one of the sources causing investor herd behaviour is investor sentiment. Comparing the closed-end fund and open-ended funds, it appears that investor sentiment has a long effect on open-ended fund managers herd behaviour, as more larger order lagged terms of sentiment coefficients are statistically significant in the open-ended fund regressions.

Table 6.3A: Weekly regression results of Open-ended funds herding on UK investor sentiment

Table 6.3A reports the results of regressions of the following general form:

$$H_t = \alpha_0 + \sum_{j=1}^{5} \alpha_j H_{t-j} + \sum_{i=0}^{5} \beta_i SENT_{t-i} + \sum_{i=0}^{5} \gamma_i SENT_{t-i}^{p} + \varepsilon_t$$

The data are weekly and cover the period 1st January 1996 to 30th June 2011. The estimation method is OLS with Newey-West standard errors

Variable definitions:

H= ***$CSAD_{op}$*, *$CSSD_{op}$* or $DHSH_{op}$**; so, $CSAD_{op}$ is Cross Section Absolute Deviation of UK open-ended funds; $CSSD_{op}$ is Cross Section Standard Deviation of UK open-ended funds; HSH_{op} is the herding measure generated by Hwang and Salmon (2004) approach from UK open-ended funds; $DHSH_{op}$ is the first order of HSH_{op}; **SENT**: UK market sentiment; **$SENT^P$**: UK institutional sentiment. **S.E**:Standard Error of regression; **AIC**: Akaike information criterion; **LM**: Breusch/Godfrey LM test for residual autocorrelation; **ARCH**: ARCH test for Heteroskadasticity. t-statistics are given in parentheses.

The model is estimated by using OLS with Newey-West HAC standard errors and covariance.

***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

	$CSAD_{op}$		$CSSD_{op}$		$DHSH_{op}$
	Model 1	**Model 2**	**Model 1**	**Model 2**	
α_0	0.9294*** (7.5719)	1.1121*** (12.1687)	1.1204*** (7.5965)	1.3386*** (12.6641)	-0.00498** (-2.3043)
α_1	0.2755*** (5.7723)	0.2945*** (6.5463)	0.2715*** (5.7575)	0.2943*** (6.7462)	0.00345 (0.0944)
α_2	0.0484 (0.9631)		0.0660 (1.2981)		-0.00480 (-0.1361)
α_3	0.0171 (0.3268)		0.0138 (0.2770)		-0.03112 (-0.8015)
α_4	0.0447 (0.9030)		0.0486 (1.0313)		-0.07017* (-1.7908)
α_5	0.0144 (0.2314)		0.0120 (0.1989)		0.04041 (1.2345)
$SENT_t$	-0.0067*** (-4.3131)	-0.0068*** (-4.5187)	-0.0075*** (-4.5252)	-0.0073*** (-4.5885)	0.00012* (1.8180)
$SENT_{t-1}$	0.0058*** (2.8653)	0.0056*** (2.8519)	0.0063*** (2.9934)	0.0047*** (3.1958)	0.00001 (0.0891)
$SENT_{t-2}$	-0.0012 (-0.6911)	-0.0016 (-0.8662)	-0.0014 (-0.6980)		0.00001 (0.0778)
$SENT_{t-3}$	0.0023 (1.4007)	0.0025 (1.4312)	0.0023 (1.2278)		-0.00002 (-0.2391)
$SENT_{t-4}$	-0.0027* (-1.7414)	-0.0028** (-2.1788)	-0.0022 (-1.2430)		0.00010 (1.1770)
$SENT_{t-5}$	-0.0001 (-0.0966)		-0.0005 (-0.3712)		-0.00010* (-1.7933)
$SENT^P_{t}$	-0.1980*** (-2.7964)	-0.1937*** (-3.0439)	-0.2264*** (-2.8903)	-0.2273*** (-3.333)	0.00507** (2.2685)
$SENT^P_{t-1}$	0.0172 (0.2013)	0.0084 (0.1219)	-0.0046 (-0.0476)	-0.0285 (-0.377)	0.00046 (0.1969)
$SENT^P_{t-2}$	-0.0378 (-0.6178)	-0.0609 (-1.1170)	-0.0343 (-0.5023)	-0.0793 (-1.312)	-0.00369 (-1.4996)
$SENT^P_{t-3}$	-0.0888* (-1.7863)	-0.0935* (-1.8227)	-0.0900 (-1.5887)	-0.1062* (-1.897)	0.00047 (0.1741)
$SENT^P_{t-4}$	-0.0025 (-0.0320)		-0.0159 (-0.1929)		0.00049 (0.2052)
$SENT^P_{t-5}$	0.0405 (0.5396)		0.0454 (0.5438)		-0.00365* (-1.7432)
Adj. R^2	0.3239	0.3255	0.3619	0.3605	0.0352
S.D.	0.4777	0.4772	0.5164	0.5166	0.01963
AIC	1.3826	1.3717	1.5384	1.5269	-5.0011
LM	1.6447***	1.6034***	1.5277**	1.5887***	4.2610***
ARCH	30.3503***	30.4727***	25.9671***	25.6445***	1.3179

Table 6.3B: Weekly regression results of Closed-end funds herding on UK investor sentiment

Table 6.3B reports the results of regressions of the following general form:

$$H_t = \alpha_0 + \sum_{j=1}^{5} \alpha_j H_{t-j} + \sum_{i=0}^{5} \beta_i SENT_{t-i} + \sum_{i=0}^{5} \gamma_i SENT_{t-i}^{p} + \varepsilon_t$$

The data are weekly and cover the period 1st January 1996 to 30th June 2011. The estimation method is OLS with Newey-West standard errors

Variable definitions:

H= ***$CSAD_{cl}$*, *$CSSD_{cl}$* or $DHSH_{cl}$**; so, $CSAD_{cl}$ is Cross Section Absolute Deviation of UK closed-end funds; $CSSD_{cl}$ is Cross Section Standard Deviation of UK closed-end funds; HSH_{cl} is the herding measure generated by Hwang and Salmon (2004) approach from UK closed-end funds; **SENT**: UK market sentiment; **$SENT^P$**: UK institutional sentiment. **S.E**:Standard Error of regression; **AIC**: Akaike information criterion; **LM**: Breusch/Godfrey LM test for residual autocorrelation; **ARCH**: ARCH test for Heteroskadasticity. t-statistics are given in parentheses.

The model is estimated by using OLS with Newey-West HAC standard errors and covariance.

***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

	$CSAD_{cl}$		$CSSD_{cl}$		HSH_{cl}	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
α_0	1.3983*** (6.0194)	1.5388*** (12.1889)	1.5254*** (5.6519)	1.5498*** (5.7590)	-0.0094*** (-3.6087)	-0.0098*** (-4.0157)
α_1	0.2088*** (4.8233)	0.2171*** (5.9560)	0.2555*** (7.4169)	0.2586*** (7.7135)	0.9549*** (26.6951)	0.9465*** (83.1838)
α_2	0.1138 (1.6144)	0.1206 (3.2807)	0.1072** (2.0222)	0.1055* (1.9533)	-0.0560 (-1.1331)	
α_3	0.0272 (0.6667)		0.0458 (1.1675)	0.0442 (1.1500)	0.0318 (0.6447)	
α_4	0.0328 (0.8863)		0.0851** (2.2989)	0.0928*** (3.0025)	0.0028 (0.0575)	
α_5	0.0254 (0.6056)		0.0224 (0.4941)		0.0175 (0.4935)	
$SENT_t$	-0.0075*** (-3.9906)	-0.0072*** (-4.2406)	-0.0089*** (-3.6328)	-0.0088*** (-3.7149)	0.0002*** (3.1683)	0.0002*** (3.4972)
$SENT_{t-1}$	0.0046** (2.0690)	0.0044*** (2.6015)	0.0052* (1.6656)	0.0060*** (2.7785)	-0.0001 (-1.0065)	-0.0001 (-1.0736)
$SENT_{t-2}$	0.0011 (0.5048)		0.0011 (0.4215)		0.0001 (0.5705)	
$SENT_{t-3}$	0.0002 (0.0866)		0.0012 (0.4335)		0.00003 (0.3649)	
$SENT_{t-4}$	-0.0016 (-0.7901)		-0.0011 (-0.3948)		-0.00001 (-0.1241)	
$SENT_{t-5}$	0.0002 (0.1518)		-0.0007 (-0.3173)		-0.00004 (-0.5563)	
$SENT^P_{t}$	-0.2709*** (-2.5300)	-0.2826*** (-4.5278)	-0.2530*** (-1.8265)	-0.2587** (-2.4848)	0.0051* (1.9426)	0.0044* (1.7125)
$SENT^P_{t-1}$	-0.1733 (-1.3586)	-0.2036** (23.0493)	-0.1821 (-1.1843)	-0.1922** (-1.9661)	0.0031 (1.1437)	0.0041 (1.5595)
$SENT^P_{t-2}$	0.1072 (1.0316)		0.0935 (0.7132)		-0.0042 (-1.5083)	-0.0040 (-1.5289)
$SENT^P_{t-3}$	-0.0200 (-0.2550)		0.0018 (0.0193)		-0.0028 (-1.0256)	-0.0025 (-1.0298)
$SENT^P_{t-4}$	-0.0411 (-0.5365)		-0.0959 (-0.7261)		0.0027 (0.9790)	
$SENT^P_{t-5}$	-0.0317 (-0.3139)		0.0045 (0.0359)		-0.0022 (-0.8356)	
Adj. R^2	0.3705	0.3731	0.3760	0.3803	0.9262	0.9261
S.D.	0.5940	0.5924	0.7842	0.7813	0.0232	0.0232
AIC	1.8184	1.7995	2.3739	2.3554	-4.6648	-4.6787
LM	1.9693***	1.9528***	2.1937***	2.0233***	0.6726	0.6871
ARCH	17.1022***	23.0493***	5.8468***	6.8010***	1.1240	1.4823

6.2.2. UK institutional herding and foreign investor sentiment

Empirical study in Chapter 3 shows that investor sentiment is contagious across borders. More especially, US investor sentiment has a significant effect on UK investor sentiment and UK equity return. The correlation tests and Granger Causality tests also reveal that US individual and institutional sentiment may cause UK institutional investor sentiment. The model (model1) to be estimated is started by including 5 lags of sentiment terms in the regression with lagged control variables:

$$H_t = \alpha_0 + \sum_{j=1}^{5} \alpha_j H_{t-j} + \sum_{i=0}^{5} \beta_i SENT_{t-i} + \sum_{i=0}^{5} \gamma_i SENT_{t-i}^{p} + \sum_{i=0}^{5} \delta_i AAII_{t-i} + \sum_{i=0}^{5} \theta_i II_{t-i} + \varepsilon_t \tag{6.2}$$

whereH_t is the level of investor's herding behaviour at time t, and it is measured by $CSAD$, $CSSD$, or HSH. The estimations start by applying OLS method, but the residual correlation and Heteroskedasticity tests show that residuals are series correlated and heteroscedastic and the estimations are adjusted accordingly by Newey-West HAC Standard Errors & Covariance. The estimated coefficients of model 1(see Table 6.4A, and Table 6.4B) show that many of the high order lagged term of variables are statistically insignificant. The models are therefore are amended by dropping some of the insignificant high order lagged variables becoming model 2.

The regression of $CSAD_{op}$ and $CSSD_{op}$generate very similar results. Coefficients, $SENT_t$, $SENT_{t-1}$, $SENT_t^p$, $SENT_{t-3}^p and\ AAII_t$ are significant, demonstrating that UK institutional herding is influenced by investor sentiment, both domestic and foreign. The negative coefficient of $SENT_t$, $SENT_t^p$ and $AAII_t$ suggests that current high investor sentiment will lead to high levels of institutional herd behaviour. The negative and significant $SENT_{t-3}^p$ shows that UK institutional sentiment has a long term effect on UK institutional herd behaviour.

When herding is measured by $DHSH_{op}$, coefficients, $SENT_{t-5}$, $SENT_t^p$, $SENT_{t-5}^p$, $II_{t-1}$and II_{t-2} are statistically significant, suggesting that UK market, UK institutional and US institutional sentiment have an impact on UK institutional herding. The positive value of estimated $SENT_t^p$ and II_{t-1}indicates that high institutional investor sentiment leads to high levels of institutional herding.

The regression of $CSAD_{cl}$and $CSSD_{cl}$suggests similar results to those of open-ended funds. Both domestic and foreign investor sentiment have an impact on UK institutional herding. However, herding of closed-end fund managers are not affected by US institutional investor sentiment, and the effect from US individual investor sentiment is less significant than that of open-ended fund managers. Unlike open-ended fund, closed-end funds do not have the constant capital injection and/or withdrawal. They are more likely make investment decisions according to public information and analysed private information which less likely to be influenced by the wider range of investor sentiment. Managers of open-ended fund, however, have to take their clients' thoughts into account when make investment decisions. The majority open-ended funds are retail funds with clients dominantly being individual investors who are affected by a wider range of investor sentiment, such as foreign investor sentiment.

Regression ofHSH_{cl}, coefficients, $SENT_t$, $SENT_t^p$ and $AAII_t$ are significant, suggesting that current UK market, UK institutional and US individual sentiment have an impact on UK institutional herding. The positive values of these coefficients indicate that high investor sentiment leads to a high level of institutional herding. As opposed to open-ended funds, the significance of US individual sentiment is rather high, which suggests that herding of closed-end fund managers is affected by foreign sentiment. This indicates that closed-ended fund managers are influenced by a wider range of investor sentiment when they consider the systematic risk of portfolio, i.e. portfolio beta.

Table 6.4A: Weekly regression results of open-ended herding on investor sentiment

Table 6.4A reports the results of regressions of the following general form:

$$H_t = \alpha_0 + \sum_{j=1}^{5} \alpha_j H_{t-j} + \sum_{i=0}^{5} \beta_i SENT_{t-i} + \sum_{i=0}^{5} \gamma_i SENT_{t-i}^{p} + \sum_{i=0}^{5} \delta_i AAII_{t-i} + \sum_{i=0}^{5} \theta_i II_{t-i} + \varepsilon_t$$

Variable definitions:
H= ***$CSAD_{op}$*, *$CSSD_{op}$* or $DHSH_{op}$**; so, $CSAD_{op}$ is Cross Section Absolute Deviation of UK open-ended funds; $CSSD_{op}$ is Cross Section Standard Deviation of UK open-ended funds; HSH_{op} is the herding measure generated by Hwang and Salmon (2004) approach from UK open-ended funds; $DHSH_{op}$ is the first order of HSH_{op}; **SENT**: UK market sentiment; **$SENT^P$**: UK institutional sentiment. AAII is American Association of Individual Investors index; II is Investors Intelligence index. t-statistics are given in parentheses.
The model is estimated by using OLS with Newey-West HAC standard errors and covariance. The data cover the period 1st January 1996 to 30th June 2011.
***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

	$CSAD_{op}$		$CSSD_{op}$		$DHSH_{op}$	
	Model 1	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**
α_0	0.9939*** (7.4934)	1.1217*** (12.3681)	1.1645*** (7.2602)	1.3678*** (12.8047)	-0.004953** (-2.3326)	-0.00525** (-2.3910)
α_1	0.2605*** (5.5261)	0.2686*** (6.6080)	0.2609*** (5.7137)	0.2748*** (6.3672)	0.005201 (0.1426)	0.00094 (0.0259)
α_2	0.0339 (0.6603)		0.0563 (1.0848)		0.002413 (0.0679)	-0.00258 (-0.0722)
α_3	0.0108 (0.2117)		0.0117 (0.2387)		-0.037921 (-0.9499)	-0.03450 (-0.8862)
α_4	0.0320 (0.6739)		0.0375 (0.8150)		-0.081198** (-2.1074)	-0.08007** (-2.0667)
α_5	0.0139 (0.2202)		0.0157 (0.2560)		0.034857 (1.0351)	
$SENT_t$	-0.0050*** (-3.2223)	-0.0047*** (-3.3785)	-0.0055*** (-3.3044)	-0.0054*** (-3.6201)	0.000046 (0.6648)	0.00004 (0.5202)
$SENT_{t-1}$	0.0052*** (2.6341)	0.0042*** (2.9709)	0.0057*** (2.7257)	0.0047*** (-3.1652)	0.000014 (0.1674)	0.00001 (0.0657)
$SENT_{t-2}$	-0.0010 (-0.5470)		-0.0011 (-0.5448)		0.000050 (0.6210)	0.00004 (0.5353)
$SENT_{t-3}$	0.0024 (1.3935)		0.0024 (1.2091)		-0.000004 (-0.0460)	0.00001 (0.0977)
$SENT_{t-4}$	-0.0025 (-1.5962)		-0.0023 (-1.2635)		0.000080 (0.9330)	0.00010 (1.2465)
$SENT_{t-5}$	0.0001 (0.0907)		-0.0002 (-0.1619)		-0.000112** (-2.0533)	-0.00011** (-2.0917)
$SENT^P_t$	-0.2053*** (-3.0507)	-0.2048*** (-3.6252)	-0.2277*** (-3.0402)	-0.2313*** (-3.6292)	0.005134** (2.2862)	0.00501** (2.2350)
$SENT^P_{t-1}$	0.0117 (0.1399)	0.0084 (0.1294)	-0.0110 (-0.1167)	-0.0234 (-0.3206)	-0.000248 (-0.1030)	-0.00011 (-0.0467)
$SENT^P_{t-2}$	-0.0514 (-0.8621)	-0.0718 (-1.4086)	-0.0410 (-0.6091)	-0.0791 (-1.3082)	-0.003115 (-1.2758)	-0.00330 (-1.3411)
$SENT^P_{t-3}$	-0.0962* (-1.9134)	-0.0942* (-1.9347)	-0.0957* (-1.6689)	-0.1010* (-1.8443)	0.001166 (0.4297)	0.00103 (0.3812)
$SENT^P_{t-4}$	-0.0091 (-0.1144)		-0.0256 (-0.3103)		-0.000210 (-0.0907)	0.00027 (0.1173)
$SENT^P_{t-5}$	0.0461 (0.6306)		0.0534 (0.6564)		-0.004133* (-1.9061)	-0.00400* (-1.9044)
$AAII_t$	-0.3030** (-2.0092)	-0.3541*** (-3.0201)	-0.2820* (-1.7141)	-0.3068** (-2.4882)	0.005112 (0.8810)	0.00499 (0.8693)
$AAII_{t-1}$	-0.0693 (-0.4713)		-0.1229 (-0.7424)		0.000983 (0.1622)	0.00119 (0.2021)
$AAII_{t-2}$	0.1157 (0.7031)		0.2050 (1.1048)		0.006277 (1.1045)	0.00586 (1.0507)
$AAII_{t-3}$	-0.0692 (-0.4388)		-0.0868 (-0.5093)		-0.007964 (-1.3100)	-0.00623 (-1.0534)
$AAII_{t-4}$	0.0558 (0.3606)		0.0390 (0.2328)		-0.010496* (-1.8070)	-0.00691 (-1.2665)
$AAII_{t-5}$	-0.0878 (-0.6507)		-0.0171 (-0.1120)		0.006104 (1.2715)	
II_t	-0.7707* (-1.8164)	-0.3304 (-1.6465)	-0.7065 (-1.6430)	-0.3938* (-1.9309)	-0.000264 (-0.0160)	-0.00079 (-0.0478)
II_{t-1}	0.6503 (1.2674)		0.6040 (1.1040)		0.042614* (1.8071)	0.04234* (1.8032)
II_{t-2}	-0.0258 (-0.0463)		-0.2431 (-0.3897)		-0.035144 (-1.5489)	-0.03047* (-1.8341)
II_{t-3}	-0.2083 (-0.3559)		-0.1781 (-0.2896)		-0.014888 (-0.6560)	
II_{t-4}	-0.1344 (-0.2514)		-0.0356 (-0.0629)		0.025818 (1.2357)	
II_{t-5}	0.2451 (0.5515)		0.2575 (0.5478)		-0.005630 (-0.3479)	
Adj. R^2	0.3353	0.3426	0.3619	0.3747	0.0430	0.0439
S.D.	0.4750	0.4708	0.5164	0.5110	0.0196	0.0196
AIC	1.3859	1.3438	1.5384	1.5076	-4.9893	-4.9973
LM	1.5151**	1.5091**	1.5277**	1.5021**	3.7976***	2.8759**
ARCH	29.5854***	29.6164***	25.9671***	25.1837***	1.5562	1.5002

Table 6.4B: Weekly regression results of closed-end herding on investor sentiment

Table 6.4B reports the results of regressions of the following general form:

$$H_t = \alpha_0 + \sum_{j=1}^{5} \alpha_j H_{t-j} + \sum_{i=0}^{5} \beta_i SENT_{t-i} + \sum_{i=0}^{5} \gamma_i SENT_{t-i}^{p} + \sum_{i=0}^{5} \delta_i AAII_{t-i} + \sum_{i=0}^{5} \theta_i II_{t-i} + \varepsilon_t$$

Variable definitions:
H= ***$CSAD_{cl}$*, *$CSSD_{cl}$* or $DHSH_{cl}$**; so, $CSAD_{cl}$ is Cross Section Absolute Deviation of UK closed-end funds; $CSSD_{cl}$ is Cross Section Standard Deviation of UK closed-end funds; HSH_{cl} is the herding measure generated by Hwang and Salmon (2004) approach from UK closed-end funds;; **SENT**: UK market sentiment; **$SENT^P$**: UK institutional sentiment. AAII is American Association of Individual Investors index; II is Investors Intelligence index. t-statistics are given in parentheses. The model is estimated by using OLS with Newey-West HAC standard errors and covariance.The data cover the period 1st January 1996 to 30th June 2011.
***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

	$CSAD_{cl}$		$CSSD_{cl}$		HSH_{cl}	
	Model 1	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**
α_0	1.3898*** (5.9040)	1.5491*** (6.7097)	1.5428*** (5.5853)	1.5930*** (5.7964)	-0.0099*** (-3.7392)	-0.0118*** (-5.4280)
α_1	0.2043*** (4.9338)	0.2105*** (4.8980)	0.2531*** (7.4026)	0.2541*** (7.7540)	0.9544*** (26.4621)	0.9348*** (82.7857)
α_2	0.1118 (1.5771)	0.1190 (1.5497)	0.1030* (1.9321)	0.1019* (1.8609)	-0.0618 (-1.2423)	
α_3	0.0249 (0.5906)		0.0392 (0.9894)	0.0371 (0.9239)	0.0351 (0.7063)	
α_4	0.0378 (0.9589)		0.0928** (2.4656)	0.0979*** (3.0535)	0.0013 (0.0265)	
α_5	0.0311 (0.7034)		0.0227 (0.4662)		0.0140 (0.3925)	
$SENT_t$	-0.0049** (-2.3050)	-0.0057*** (-2.9336)	-0.0054* (-1.9499)	-0.0052** (-2.0862)	0.0002** (2.1370)	0.0001*** (3.2703)
$SENT_{t-1}$	0.0037 (1.6418)	0.0044** (2.5799)	0.0031 (0.9769)	0.0037 (1.5849)	-0.0001 (-0.9939)	
$SENT_{t-2}$	0.0008 (0.3660)		0.0016 (0.5717)		0.0001 (0.9421)	
$SENT_{t-3}$	0.0002 (0.1115)		0.0014 (0.4636)		0.00003 (0.3445)	
$SENT_{t-4}$	-0.0024 (-1.1635)		-0.0029 (-1.0009)		-0.00004 (-0.4555)	
$SENT_{t-5}$	0.0008 (0.4921)		0.0002 (0.1101)		-0.00003 (-0.4927)	
$SENT^P_t$	-0.2660*** (-2.6035)	-0.2784*** (-3.2540)	-0.2512** (-1.9149)	-0.2526** (-2.4591)	0.0058** (2.1631)	0.0045** (2.1937)
$SENT^P_{t-1}$	-0.1886 (-1.4646)	-0.2042** (-2.4356)	-0.1997 (-1.3033)	-0.1874* (-1.8907)	0.0027 (0.9876)	
$SENT^P_{t-2}$	0.1077 (1.0366)		0.1012 (0.7678)		-0.0031 (-1.1138)	
$SENT^P_{t-3}$	-0.0159 (-0.1962)		0.0078 (0.0818)		-0.0019 (-0.6872)	
$SENT^P_{t-4}$	-0.0505 (-0.6475)		-0.1034 (-0.7977)		0.0024 (0.8625)	
$SENT^P_{t-5}$	-0.0043 (-0.0425)		0.0379 (0.3064)		-0.0021 (-0.7885)	
$AAII_t$	-0.2391 (-1.4846)	-0.1576 (-1.0257)	-0.3255 (-1.3250)	-0.3437 (-1.4183)	0.0119* (1.8104)	0.0153** (2.4973)
$AAII_{t-1}$	-0.3002 (-1.5296)	-0.1167 (-0.6631)	-0.2903 (-1.0934)	-0.2680 (-1.0198)	-0.0025 (-0.3551)	-0.0015 (-0.2252)
$AAII_{t-2}$	0.2513 (1.1157)		0.4744 (1.5814)	0.4380 (1.5538)	0.0100 (1.3806)	0.0076 (1.1163)
$AAII_{t-3}$	-0.0133 (-0.0604)		-0.1200 (-0.4139)	-0.0438 (-0.1596)	-0.0049 (-0.6688)	-0.0047 (-0.7018)
$AAII_{t-4}$	-0.0038 (-0.0188)		-0.0299 (-0.1160)	0.0235 (0.0919)	-0.0075 (-1.0525)	-0.0089 (-1.3390)
$AAII_{t-5}$	0.2890 (1.5161)		0.5003** (2.0581)	0.3841* (1.8164)	0.0109 (1.6403)	0.0095 (1.5853)
II_t	-0.2911 (-0.6018)	-0.4128 (-0.8976)	-0.3012 (-0.4354)	-0.2647 (-0.3765)	0.0092 (0.4856)	-0.0048 (-0.5589)
II_{t-1}	0.1625 (0.2088)	0.1532 (0.2956)	-0.2382 (-0.2491)	-0.3575 (-0.5101)	0.0128 (0.4706)	
II_{t-2}	-0.4246 (-0.6036)		0.1729 (0.1782)		-0.0237 (-0.8584)	
II_{t-3}	0.1828 (0.2446)		-0.4957 (-0.4252)		-0.0249 (-0.9037)	
II_{t-4}	0.0900 (0.1293)		0.2119 (0.2178)		0.0290 (1.0523)	
II_{t-5}	-0.0766 (-0.1289)		0.0382 (0.0502)		-0.0080 (-0.4049)	
Adj. R^2	0.3738	0.3771	0.3810	0.3872	0.9272	0.9277
S.D.	0.5946	0.5913	0.7834	0.7795	0.0232	0.0231
AIC	1.8351	1.8005	2.3866	2.3607	-4.6567	-4.6863
LM	1.6817***	1.9085***	1.6021***	1.4353***	0.7239	0.5820
ARCH	14.2953***	22.2884***	5.0132***	5.7806	1.0193	1.3204

6.2.3. Sentiment effect on herding in different financial crisis stages

As pointed out in previous sections, investor sentiment is more likely to influence investors' decision making during market extreme times, more precisely the financial or economic crisis time. What about the relation between investor herd behaviour and investor sentiment under the different market conditions? Are investors more likely to herd on investor sentiment in the normal time, crisis time, or when the market is in the bubble generating period? The sample period of 1996-2011 has experienced several major economic and financial crises; therefore the sentiment effects in the crisis time can be investigated by using the same defined pre and in-crisis times. This is done by regressing herding measures on $SENT$ and $SENT^p$ under three conditions: non-crisis period, pre-crisis periods, and in-crisis periods respectively. The model is:

$$\begin{aligned} H_t = {} & \alpha_1^{no-cri} D_1 + \alpha_2^{no-cri} H_{t-1} * D_1 + \sum_{i=0}^{2} \beta_i^{no-cri} SENT_{t-i} * D_1 + \sum_{i=0}^{2} \gamma_i^{no-cri} SENT_{t-i}^p \\ & * D_1 + \alpha_1^{pre-cri} D_2 + \alpha_2^{pre-cri} H_{t-1} * D_2 + \sum_{i=0}^{2} \beta_i^{pre-cri} SENT_{t-i} * D_2 \\ & + \sum_{i=0}^{2} \gamma_i^{pre-cri} SENT_{t-i}^p * D_2 + \alpha_1^{in-cri} D_3 + \alpha_2^{in-cri} H_{t-1} * D_3 \\ & + \sum_{i=0}^{2} \beta_i^{in-cri} SENT_{t-i} * D_3 + \sum_{i=0}^{2} \gamma_i^{in-cri} SENT_{t-i}^p * D_3 + \varepsilon_t \end{aligned} \quad (6.3)$$

Where the superscripts *nor-cri, pre-cri* and *in-cri* refer to no-crisis, pre-crisis and in crisis periods respectively; H_t is the institutional herding measures of $CSAD$, $CSSD$, or $DHSH_{op}$ $(or\ HSH_{cl})$. $D_1 = 1$in non-crisis periods and zero otherwise; $D_2 = 1$ in pre-crisis periods and zero otherwise; $D_3 = 1$ for in-crisis periods and zero otherwiseThe regression results are displayed in Table 6.5A and Table 6.5B.

During the normal period, the regressions of return dispersion (CSAD and CSSD)generate very similar results for both open-ended funds and closed-end funds. The significance ofβ_0^{no-cri}, $\beta_1^{no-cri}$and γ_0^{no-cri} demonstrate that market and institutional sentiment have some explanatory power to institutional herd behaviour. The opposite sign of β_0^{no-cri} andβ_1^{no-cri}suggests the 'second thought' effect on institutional herding. Regressions of HSH show that institutional herding is affected by institutional sentiment in both categories of funds, which is consistent with the suggestion from CSAD and CSSD. However, market sentiment has no significant effect on open-ended fund manager's herding on market Beta. This is because returns of the funds are normally to be used as a measure to assess open-ended fund managers' performance by their clients. In order to satisfy their clients expected returns, fund managers are more likely to concentrate on the market return rather than the beta of the equity.

During pre-crisis period, regressions of return dispersion ($CSAD_{op}$and $CSSD_{op}$) and beta herding of open-ended funds ($DHSH_{op}$) display similar pictures. The significance of coefficients of $\beta_0^{pre-cri}$and insignificance of$\gamma^{pre-cri}$s suggest that institutional herding during a pre-crisis period is mainly caused by market sentiment rather than institutional sentiment. This corresponds to estimates of HSH_{cl}, which demonstrate that market sentiment rather than institutional sentiment has some explanatory power to beta herding of closed-end fund managers. However, return dispersions of closed-end funds ($CSAD_{cl}$and $CSSD_{cl}$) reveal a different picture. Both market and institutional sentiment have effect on institutional herding behaviour, and institutional sentiment has a higher significant level effect than that of individual sentiment. This may be able to be explained by the majority investors of closed-end funds being institutional investors.

During the crisis period, regressions of beta herding (HSH) from both open-ended and closed-end funds demonstrate that herding during crisis period is not caused by investor sentiment. This suggests that investors in this period are more likely to herd on public information and asset fundamentals. This, again, corresponds with the suggestion that financial crisis is the process of adjusting asset prices to their fundamental. Estimates of return dispersions (CSAD and CSSD), however, show different features. Coefficients suggest that market and institutional sentiment has some effect on institutional herding behaviour, though the significant level of institutional sentiment is rather low for closed-end funds, between 5% to 10% significant levels, and it is high for open-ended funds, between 1% to 5% significant levels. This, once again, demonstrates that differences between open-ended and closed-end funds can lead to the manager of a fund following different factors when he/she forms the investor portfolio.

In general, estimates of return dispersion from both open-ended funds and closed-end funds suggest that institutional herding on returns is affected by both market and institutional sentiment in all period. During no-crisis, i.e. normal period, there is a reverse effect from market sentiment. During pre-crisis, market sentiment is one of the factors causing institutional herding behaviour, and institutional sentiment has no significant effect on it, especially for open-ended funds. Herding on beta of closed-end funds (HSH_{cl}) also displays such characteristics. Herding on returns of closed-end funds however, is still influenced by both market and institutional sentiment and there is an implication of a higher degree of effect from institutional sentiment than that from market sentiment. During the crisis period, investor sentiment has no effect on beta herding, suggesting institutional herding in this period may be caused by fundamental factors. Return herding, on the other hand, still appears to be affected by both market and institutional sentiment. Market sentiment has a greater effect on closed-end fund return herding and institutional sentiment influences open-ended fund return herding to a greater level.

The examination of investor sentiment effect on herding behaviour in different financial crisis stages demonstrates that investor sentiment generally affects institutional herding behaviour in all stages of financial crisis. However, sentiment from different groups of investors has a different degree of effect on herding behaviour according to the stage and what factor managers herd on. Different categories of mutual funds can also cause the differences in the effect from investor sentiment because of the structure of the fund, investor group of the fund, and the market environment of the fund. The analysis of investor sentiment effect on institutional herding in different stages of financial crises not only gives evidence that investor sentiment is a significant factor in explaining institutional herd behaviour, but also identifies the sentiment effects that come from different group's of investors under different conditions.

Table 6.5A: weekly regression open-ended funds herding on investor sentiment under financial crisis conditions

Table 6.5A reports the results of regressions of the following general form:

$$H_t = \alpha_1^{no-cri} D_1 + \alpha_2^{no-cri} H_{t-1} * D_1 + \sum_{i=0}^{2} \beta_i^{no-cri} SENT_{t-i} * D_1 + \sum_{i=0}^{2} \gamma_i^{no-cri} SENT_{t-i}^{p} * D_1 + \alpha_1^{pre-cri} D_2 + \alpha_2^{pre-cri} H_{t-1} * D_2 + \sum_{i=0}^{2} \beta_i^{pre-cri} SENT_{t-i} * D_2 + \sum_{i=0}^{2} \gamma_i^{pre-cri} SENT_{t-i}^{P} * D_2 + \alpha_1^{in-cri} D_3 + \alpha_2^{in-cri} H_{t-1} * D_3 + \sum_{i=0}^{2} \beta_i^{in-cri} SENT_{t-i} * D_3 + \sum_{i=0}^{2} \gamma_i^{in-cri} SENT_{t-i}^{p} * D_3 + \varepsilon_t$$

Variable definitions:

H= ***CSAD***$_{op}$**,** ***CSSD***$_{op}$ **or DHSH**$_{op}$; so, CSAD$_{op}$ is Cross Section Absolute Deviation of UK open-ended funds; CSSD$_{op}$ is Cross Section Standard Deviation of UK open-ended funds; HSH$_{op}$ is the herding measure generated by Hwang and Salmon (2004) approach from UK open-ended funds; DHSH$_{op}$ is the first order of HSH$_{op}$; **SENT**: UK market sentiment; **SENT**^{P}: UK institutional sentiment. t-statistics are given in parentheses. D_1 = 1 in non-crisis periods and zero otherwise; D_2 = 1 in pre-crisis periods and zero otherwise; D_3 = 1 in in-crisis periods and zero otherwise. The pre- and in-crisis periods are as defined in Appendix 2. The no-crisis periods consist of the remaining observations in the sample.

The model is estimated by using OLS with Newey-West HAC standard errors and covariance.
***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

	CSAD$_{op}$				CSSD$_{op}$				DHSH$_{op}$		
Coefficients	Normal period	pre-crisis period	in-crisis period		Normal period	pre-crisis period	in-crisis period		Normal period	pre-crisis period	in-crisis period
α_1	1.1719*** (9.7051)	0.8711*** (5.9607)	0.7519*** (4.1282)		1.3880*** (10.3002)	1.2363*** (7.5273)	1.0045*** (4.2203)		-0.0050*** (-2.0619)	-0.0201*** (-2.25981)	0.0022 (0.4284)
α_2	0.2756*** (4.6504)	0.2783*** (3.7839)	0.2769*** (3.5266)		0.2885*** (5.0059)	0.2624*** (3.5299)	0.2730*** (3.0530)		0.0130 (0.2902)	-0.1916** (-2.3194)	0.0441 (0.6271)
$SENT_t$	-0.0077*** (-3.6146)	-0.0044** (-2.2658)	-0.0029 (-0.8467)		-0.0083*** (-3.6251)	-0.0061** (-2.5699)	-0.0028 (-0.7868)		0.00002 (0.3583)	0.0005*** (3.4440)	0.0002 (1.4998)
$SENT_{t-1}$	0.0079*** (2.8456)	0.0057*** (2.7707)	-0.0016 (-0.3764)		0.0079*** (2.6794)	0.0086*** (3.5344)	-0.0023 (-0.5361)		0.00003 (0.3256)	-0.0002 (-1.0198)	0.0001 (0.6487)
$SENT_{t-2}$	-0.0032* (-1.8565)	-0.0028 (-1.3515)	0.0049* (1.8171)		-0.0031* (-1.6480)	-0.0047* (-1.7329)	0.0058** (2.2159)		0.00004 (0.6609)	-0.00006 (-0.3710)	-0.00001 (-0.0590)
$SENT^{P}_{t}$	-0.3222*** (-4.1259)	-0.1230 (-1.5520)	0.0592 (0.5057)		-0.3605*** (-4.1343)	-0.1314 (-1.3056)	0.0410 (0.3333)		0.0069** (2.3083)	0.0047 (1.1624)	-0.0050 (-1.1923)
$SENT^{P}_{t-1}$	-0.0541 (-0.6373)	-0.0124 (-0.1503)	0.1503 (1.5039)		-0.0806 (-0.8747)	-0.1119 (-1.1840)	0.1379 (1.2033)		-0.000002 (-0.0006)	0.0039 (0.6922)	-0.0053 (-1.3093)
$SENT^{P}_{t-2}$	-0.0168 (-0.2564)	-0.0697 (-0.7292)	-0.2227** (-2.0482)		-0.0144 (-0.1772)	-0.0834 (-0.8533)	-0.2729** (-2.2427)		-0.0060** (-2.3993)	-0.0053 (-1.0495)	-0.0046 (-0.9425)

Table 6.5B: weekly regression closed-end funds herding on investor sentiment under financial crisis conditions

Table 6.5B reports the results of regressions of the following general form:

$$H_t = \alpha_1^{no-cri} D_1 + \alpha_2^{no-cri} H_{t-1} * D_1 + \sum_{i=0}^{2} \beta_i^{no-cri} SENT_{t-i} * D_1 + \sum_{i=0}^{2} \gamma_i^{no-cri} SENT_{t-i}^{p} * D_1 + \alpha_1^{pre-cri} D_2 + \alpha_2^{pre-cri} H_{t-1} * D_2 + \sum_{i=0}^{2} \beta_i^{pre-cri} SENT_{t-i} * D_2 + \sum_{i=0}^{2} \gamma_i^{pre-cri} SENT_{t-i}^{p} * D_2 + \alpha_1^{in-cri} D_3 + \alpha_2^{in-cri} H_{t-1} * D_3 + \sum_{i=0}^{2} \beta_i^{in-cri} SENT_{t-i} * D_3 + \sum_{i=0}^{2} \gamma_i^{in-cri} SENT_{t-i}^{p} * D_3 + \varepsilon_t$$

Variable definitions:
H= ***CSAD$_{cl}$*, *CSSD$_{cl}$* or DHSH$_{cl}$**; so, CSAD$_{cl}$ is Cross Section Absolute Deviation of UK closed-end funds; CSSD$_{cl}$ is Cross Section Standard Deviation of UK closed-end funds; HSH$_{cl}$ is the herding measure generated by Hwang and Salmon (2004) approach from UK closed-end funds; **SENT**: UK market sentiment; **SENT^{P}**: UK institutional sentiment. t-statistics are given in parentheses. D_1 = 1 in non-crisis periods and zero otherwise; D_2 = 1 in pre-crisis periods and zero otherwise; D_3 = 1 in in-crisis periods and zero otherwise. The pre- and in-crisis periods are as defined in Appendix 2. The no-crisis periods consist of the remaining observations in the sample.

The model is estimated by using OLS with Newey-West HAC standard errors and covariance. The data cover the period 1st January 1996 to 30th June 2011.
***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

	CSAD$_{cl}$				CSSD$_{cl}$				HSH$_{cl}$		
Coefficients	Normal period	pre-crisis period	in-crisis period		Normal period	pre-crisis period	in-crisis period		Normal period	pre-crisis period	in-crisis period
α$_1$	1.8555*** (8.3105)	1.9145*** (8.6028)	1.4709*** (6.4411)		2.2994*** (10.1105)	2.5781*** (9.0235)	1.8919*** (6.4823)		-0.0106*** (-3.3795)	-0.0095 (-1.2160)	-0.0098 (-1.6051)
α$_2$	0.2102*** (2.9432)	0.2413*** (3.5526)	0.2621*** (3.4230)		0.2609*** (4.2401)	0.3157*** (5.2228)	0.3281*** (5.1168)		0.9408*** (57.6060)	0.9116*** (30.3448)	0.9382*** (35.0586)
SENT$_t$	-0.0092*** (-3.5715)	-0.0080* (-1.9874)	-0.0013 (-0.3894)		-0.0120*** (-3.5700)	-0.0097* (-1.7795)	-0.0003 (-0.0557)		0.0002** (-1.9855)	0.0005*** (3.0837)	0.0002 (1.6283)
SENT$_{t-1}$	0.0075** (2.4665)	0.0049 (1.4225)	-0.0053 (-1.2662)		0.0099** (2.4518)	0.0065 (1.1232)	-0.0105* (-1.6792)		-0.0001 (-1.1943)	-0.0001 (-0.7330)	-0.0001 (-0.2672)
SENT$_{t-2}$	-0.0024 (-1.0809)	-0.0008 (-0.3092)	0.0064** (1.9997)		-0.0032 (-1.2297)	-0.0032 (-0.7938)	0.0115** (2.5100)		0.0001 (0.8566)	-0.00004 (-0.2760)	0.0001 (0.7677)
SENT$^{P}_{t}$	-0.4430*** (-3.2449)	-0.0960 (-0.7293)	-0.0739 (-0.5945)		-0.4375*** (-2.6086)	-0.1432 (-0.8173)	-0.0625 (-0.4031)		0.0075** (2.2970)	-0.0044 (-0.7364)	0.0006 (0.1021)
SENT$^{P}_{t-1}$	-0.2741* (-1.9255)	-0.3676*** (-2.9104)	-0.0881 (-0.4783)		-0.3401** (-2.0233)	-0.4115** (-2.3854)	-0.1157 (-0.4496)		0.0023 (0.6947)	0.0086 (1.3972)	0.0023 (0.4027)
SENT$^{P}_{t-2}$	0.1103 (0.7084)	-0.1278 (-1.0162)	-0.1269 (-1.3096)		0.0789 0.4100)	-0.2111 (-1.3363)	-0.2649* (-1.8965)		-0.0047 (-1.2160)	-0.0068 (-1.6051)	-0.0064 (-1.1353)

6.2.4. Sentiment effect on herding under different market sentiment conditions

In this part, the impact that investor sentiment has on investor herding is examined by investigating the possible asymmetric effect under different market sentiment conditions. The market wide sentiment is defined as high when the sentiment at time t is higher than its mean, i.e. $SENT_t > \overline{SENT}$, where $\overline{SENT}$ is the mean of the composed market sentiment. The market sentiment is defined as low when $SENT_t < \overline{SENT}$. Herding measures are regressed on the market sentiment, $SENT$, and the institutional sentiment, $SENT^p$ under high sentiment and low sentiment conditions. The model is:

$$H_t = \alpha_1^{high} D_1 + \alpha_2^{high} H_{t-1} * D_1 + \sum_{i=0}^{2} \beta_i^{high} SENT_{t-i} * D_1 + \sum_{i=0}^{2} \gamma_i^{high} SENT_{t-i}^{p} * D_1 + \alpha_1^{low} D_1 + \alpha_2^{low} H_{t-1} * D_2 + \sum_{i=0}^{2} \beta_i^{low} SENT_{t-i} * D_2 + \sum_{i=0}^{2} \gamma_i^{low} SENT_{t-i}^{p} * D_2 + \varepsilon_t \tag{6.4}$$

where the superscripts $high$ and low refer to high market sentiment and low market sentiment periods respectively; H_t is the herding measures of $CSAD$, $CSSD$, and $DHSH_{op}$ (or HSH_{cl}). $D_1 = 1$ when $SENT_t > \overline{SENT}$ and zero otherwise; $D_2 = 1$ when $SENT_t < \overline{SENT}$ and zero otherwise. The regression results are reported in Table 6.6.

The estimates of open-ended fund return dispersion, $CSAD_{op}$ and $CSSD_{op}$, suggest that institutional herding is more likely to be influenced by institutional sentiment rather than market sentiment when market sentiment is high since γ_2^{high} is strongly significant but $\beta^{high}s$ are not significant. Although β_1^{high} under $CSSD_{op}$ is significant at 10% level, the insignificance β_1^{high} of $CSAD_{op}$ indicates that the effect from market sentiment to open-ended funds' herding is rather weak. For closed-end funds, however, the significant of β_1^{high} demonstrates that both market and institutional sentiment has a significant effect on institutional herding.

When market sentiment is low, estimates from both open-ended funds and closed-end funds reveal very similar pictures. The significant of β_0^{low}, β_1^{low} and γ_0^{low} suggests that institutional herding is affected by both market sentiment and institutional sentiment. The test of nulls of $\beta_0^{high} = \beta_0^{low}$ and $\gamma_0^{high} = \gamma_0^{low}$ are rejected at the 5% significant level, suggesting that market sentiment and institutional sentiment have asymmetric effects on institutional herding under different market sentiment conditions. According to the value of coefficients, investor sentiment generally has a greater impact on institutional herding when market sentiment is low.

When institutional herding is measured by HSH, herding by both open-ended funds and closed-end funds is affected by market and institutional sentiment when market wide sentiment is high. However, the significant level of coefficients of open-ended funds is higher than that of closed-end funds, which may suggest that investor sentiment has a higher degree of impact on beta herding among open-ended funds when market wide sentiment is high. When market sentiment is low, estimated coefficients show that herding of open-ended funds is affected by institutional sentiment and herding of closed-end funds is affected by both market and institutional sentiment, which corresponds to the estimates in the high market sentiment condition. This can be explained by managers of open-ended funds needing to consider their clients (or potential clients)'s expectations when they form investment portfolios. Individual investors are more likely to be irrational in decision making compared to institutional investors. Therefore, managers of open-ended funds are more likely to be affected by investor sentiment to a greater degree than those of closed-end funds, whose capital does not fluctuate because of new joiners and redemptions.

The asymmetric effect on herding which is found in regressions of return dispersions cannot be found in regressions of beta herding. This suggests that investor sentiment has a symmetric effect on institutional beta herding when market wide sentiment is high or low.

Table 6.6: Weekly regression herding on investor sentiment indexes under market sentiment conditions

Table 6.6 reports the results of regressions of the following general form:

$$H_t = \alpha_1^{high} D_1 + \alpha_2^{high} H_{t-1} * D_1 + \sum_{i=0}^{2} \beta_i^{high} SENT_{t-i} * D_1 + \sum_{i=0}^{2} \gamma_i^{high} SENT_{t-i}^{p} * D_1 + \alpha_1^{low} D_1 + \alpha_2^{low} H_{t-1} * D_2 + \sum_{i=0}^{2} \beta_i^{low} SENT_{t-i} * D_2 + \sum_{i=0}^{2} \gamma_i^{low} SENT_{t-i}^{p} * D_2 + \varepsilon_t$$

Variable definitions:

H= ***CSAD, CSSD* or DHSH**; so, $CSAD_{op}$ is Cross Section Absolute Deviation of UK open-ended funds; $CSSD_{op}$ is Cross Section Standard Deviation of UK open-ended funds; HSH_{op} is the herding measure generated by Hwang and Salmon (2004) approach from UK open-ended funds; $DHSH_{op}$ is the first order of HSH_{op}; $CSAD_{cl}$ is Cross Section Absolute Deviation of UK closed-end funds; $CSSD_{cl}$ is Cross Section Standard Deviation of UK closed0end funds; HSH_{cl} is the herding measure generated by Hwang and Salmon (2004) approach from UK closed-end funds.**SENT**: UK market sentiment; **SENT^P**: UK institutional sentiment. t-statistics are given in parentheses. $D_1 = 1$when$SENT_t > \overline{SENT}$ and zero otherwise; $D_2 = 1$ when $SENT_t < \overline{SENT}$ and zero otherwise. **F1** is f-statistic of null hypothesis of $\beta_0^{high} = \beta_0^{low}$, where β_0^{high} is β_0 when $SENT_t > \overline{SENT}$ and β_0^{low} is β_0 when $SENT_t < \overline{SENT}$. **F2** is f-statistic of null hypothesis of $\beta_1^{high} = \beta_1^{low}$, where β_0^{high} is β_1 when $SENT_t > \overline{SENT}$ and β_1^{low} is β_1 when $SENT_t < \overline{SENT}$. **F3** is f-statistic of null hypothesis of $\gamma_0^{high} = \gamma_0^{low}$, where γ_0^{high} is γ_0 when $SENT_t > \overline{SENT}$ and γ_0^{low} is γ_0 when $SENT_t < \overline{SENT}$. **F4** is f-statistic of null hypothesis of $\gamma_2^{high} = \gamma_2^{low}$, where γ_2^{high} is γ_2 when $SENT_t > \overline{SENT}$ and γ_2^{low} is γ_2 when $SENT_t < \overline{SENT}$.

The model is estimated by using OLS with Newey-West HAC standard errors and covariance.The data cover the period 1st January 1996 to 30th June 2011.

***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

	Open-ended Funds						Closed-end Funds					
	$CSAD_{op}$		$CSSD_{op}$		$DHSH_{op}$		$CSAD_{cl}$		$CSSD_{cl}$		HSH_{cl}	
	High	Low	High	Low	High	Low	High	Low	High	Low	High	Low
α_1	0.8544*** (5.1652)	1.1771*** 8.6223)	1.0146*** (5.5368)	1.4449*** (9.5037)	-0.012153* (-1.7170)	-0.00584** (-2.4822)	1.2217*** (7.0254)	2.0627*** (8.3578)	1.5500*** (6.8340)	2.4630*** (9.4118)	-0.0141* (-1.6688)	-0.0106*** (-3.3829)
α_2	0.2733*** (4.3663)	0.2815*** (4.9296)	0.2920*** (4.3547)	0.2717*** (5.0458)	-0.096937** (-2.1347)	0.142210** (2.4743)	0.3392*** (5.8682)	0.1581** (2.3928)	0.3819*** (8.3316)	0.2446*** (4.2785)	0.9312*** 63.2076)	0.9635*** (53.8167)
$SENT_t$	-0.0018 (-0.7283)	-0.0102*** (-3.3542)	-0.0017 (-0.6321)	-0.0106*** (-3.1932)	0.000356*** (2.7389)	0.000125 (1.2836)	-0.0041 (-1.4300)	-0.0094** (-2.3617)	-0.0044 -1.0803)	-0.0111** (-2.1027)	0.0004** (2.3571)	0.0003** (2.5587)
$SENT_{t-1}$	0.0035 (1.5930)	0.0061* (1.7743)	0.0045* (1.8818)	0.0062* (1.7451)	-0.000095 (-0.7796)	0.000022 (0.2081)	0.0080*** (2.8119)	0.0013 (0.3759)	0.0095** (2.4385)	0.0011 (0.2218)	-0.0001 (-0.7573)	-0.0002 (-1.3913)
$SENT_{t-2}$	-0.0017 (-1.0818)	-0.0010 (-0.4380)	-0.0020 (-1.1956)	-0.0011 (-0.4268)	-0.000003 (-0.0316)	-0.000020 (-0.2472)	-0.0030 (-1.4504)	0.0023 (0.8344)	-0.0037 (-1.3802)	0.0036 (1.0003)	-0.0001 (-0.7159)	0.0002* (1.7130)
$SENT^P_t$	-0.0731 (-1.2506)	-0.3568*** (-3.8798)	-0.0733 (-1.1140)	-0.4253*** (-4.2562)	0.006180** (2.0117)	0.000937 (0.3141)	-0.0667 (-0.8049)	-0.5567*** (-3.8531)	-0.0426 (-0.4066)	-0.5675*** (-3.2546)	0.0062* (1.6947)	0.0008 (0.2137)
$SENT^P_{t-1}$	-0.0589 (-0.9267)	0.0512 (0.4963)	-0.1056 (-1.4723)	0.0300 (0.2551)	-0.003513 (-1.2090)	0.004620 (1.4163)	-0.2647*** (-3.3102)	-0.2138 (-1.1231)	-0.3316*** (-3.0083)	-0.2255 (-0.9833)	0.0024 (0.6858)	0.0055 (1.4098)
$SENT^P_{t-2}$	-0.1514*** (-2.6555)	-0.0897 (-1.1721)	-0.1849*** (-3.1784)	-0.0801 (-0.8218)	-0.006192** (-2.0031)	-0.00518* (-1.7511)	-0.1010* (-1.7027)	0.0702 (0.3915)	-0.1657* (-1.9552)	0.0134 (0.0604)	-0.0043 (-1.1700)	-0.0076** (-2.1581)
F1	4.0489**		3.8643**		2.0271		1.0844		1.0009		0.1063	
F2	0.3188		0.1333		0.5309		2.0863		1.8307		0.1044	
F3	6.4553**		8.2814***		1.4984		8.4070***		6.4337**		0.0054	
F4	0.4278		0.8742		0.0559		0.0624		0.1788			

Examination of investor sentiment effect on institutional herding presents several characteristics: firstly, it seems that current investor sentiment affects herding in the general low market sentiment period and lagged investor sentiment affects herding in the high market sentiment time. Secondly, investor sentiment asymmetric effect on herding depends on the measure of herding. Return dispersion herding measurement shows a strong asymmetric market sentiment, but beta dispersion herding measurement shows no asymmetric effect. Lastly, investor sentiment may have a different degree of effect on herding between open-ended funds and closed-end funds, but this difference is not significant and it is more likely to appear in the return dispersion measures.

6.2.5. Monthly institutional herding and Investor sentiment

The examinations of how investor sentiment affects UK institutional herding were conducted by using weekly data in previous sections. In this section, the sentiment effect on institutional herding is investigated by using monthly data. As in the weekly analysis, UK institutional herding measures, CSAD, CSSD, and HSH are examined against the two composed UK investor sentiment indexes, $SENT$ and $SENT^p$, as well as US individual and institutional sentiment indexes, AAII and II. Similar to the weekly data, the Augmented Dickey-Fuller (ADF) test of HSH_{op} (Table 6.7) cannot reject the null hypothesis of unit root, the first difference of the series, $DHSH_{op}$ is considered, and the ADF test shows that $DHSH_{op}$ is a stationary series.

The correlation tests (Table 6.8 Panel A) demonstrate that return dispersions (CSAD and CSSD) have significant correlation to UK investor sentiment and US institutional sentiment which is similar to weekly data. However, the coefficient correlation between $CSSD_{cl}$ and $SENT$ is not significant, demonstrating insignificant correlation between UK market sentiment and institutional return herding. The less significant level of $CSSD_{cl}$ may be caused by the way it is calculated. Different from weekly data, the insignificant coefficients demonstrate return dispersions of open-ended funds and closed-end funds are not correlated to US individual sentiment. The correlation coefficients of beta herding measures show very different pictures. Beta herding of open-ended funds is significantly correlated to US individual and institutional sentiment, but has no significant correlation to UK investor sentiment. However, beta herding of closed-end funds significantly correlates to UK investor sentiment, but has no significant correlation to US investor sentiment.

The Granger causality tests (Table 6.8 Panel B) show that US institutional sentiment is one of the factors to cause return herding of open-ended funds, but not cause return herding of closed-end funds. On the other hand, UK institutional sentiment is likely to be caused by institutional herding rather than vice versa for both open-ended and closed-end funds. P-values of the Granger causality tests of beta herding suggest that, except US individual sentiment which is led by open-ended fund herding, there is no clear Granger causal relation among the pairwise variables.

The investigation of whether UK investor sentiment has effects on institutional herding is conducted by using monthly data. The model is started by including 3 lagged terms of variables, and is called model 1:

$$H_t = \alpha + \sum_{j=1}^{3} \alpha_j H_{t-j} + \sum_{i=0}^{3} \beta_i SENT_{t-i} + \sum_{i=i}^{3} \gamma_i SENT_{t-i}^{p} + \varepsilon_t \tag{6.5}$$

whereH_t is the level of investor's herding behavior at time t, and it is measured by $CSAD$, $CSSD$, or $DHSH_{op}$(or HSH_{cl}). The estimation results are presented in Table 6.9A and Table 6.9B. Coefficients for the lagged term of sentiment variables are all statistically insignificant. Model 1 therefore is amended to model 2 by dropping them.

The estimated coefficients for return dispersion ($CSAD$and $CSSD$) tell similar stories for both open-ended and closed-end funds. The significant of $SENT_t^p$ demonstrates that UK institutional sentiment has an effect on UK institutional herding. The negative value suggests that a high institutional investor sentiment leads to a low level cross-section return dispersion, meaning the degree of herd behaviour is high. This echoes the estimated results from weekly data. βs are not significant, implying the UK market sentiment may not affect UK institutional herding in the monthly frequency. This may be explained by the reverse effect of market sentiment in the weekly data, which shows that the market sentiment effect on herding is reversed from one week to another week. The sentiment effect in the short run is eliminated in the long-run.

Table 6.7: Statistic summary of monthly herding and sentiment variable

AAII is American Association of Individual Investors index; GMI is German Market Indicator; II is Investors Intelligence index; SENT isUK market investor sentiment index; $SENT^p$ is UK institutional investor sentiment; $CSAD_{op}$ is Cross Section Absolute Deviation of UK open-ended funds; $CSSD_{op}$ is Cross Section Standard Deviation of UK open-ended funds; HSH_{op} is the herding measure generated by Hwang and Salmon (2004) approach from UK open-ended funds; $DHSH_{op}$ is the first order of HSH_{op}; $CSAD_{cl}$ is Cross Section Absolute Deviation of UK closed-end funds; $CSSD_{cl}$ is Cross Section Standard Deviation of UK closed0end funds; HSH_{cl} is the herding measure generated by Hwang and Salmon (2004) approach from UK closed-end funds.The data cover the period 1st January 1996 to 30th June 2011.

AC (1) is autocorrelation coefficient at one lag. **AC (2)** is autocorrelation coefficient at 2 lags. **ADF** is Augmented Dickey-Fuller test statistic with maximum 52 lags for weekly indexes and 12 lags for monthly indexes. **Obs** is number of observation. ***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

Statistical summary of monthly variables										
Variable	**Mean**	**Std. Dev.**	**Skewness**	**Kurtosis**	**Jarque-Bera**	**Sum Sq. Dev.**	**AC (1)**	**AC (2)**	**ADF**	**Obs**
AAII	0.1043	0.1984	0.1534	2.3353	4.1538	7.2809	0.429	0.279	-8.5466***	186
GMI	0.2989	0.3687	-0.4968	2.3965	10.4727***	25.1489	0.955	0.870	-3.4685***	186
II	0.1829	0.1319	-0.7156	3.3733	16.9560***	32.18934	0.695	0.456	-5.7242***	186
SENT	20.3275	10.4377	-0.1456	2.5854	1.9680	19936.92	0.821	0.665	-3.3222**	184
$SENT^p$	1.0212	0.4356	-0.8064	4.4858	37.0646***	34.9081	0.801	0.665	-4.4809***	185
$CSAD_{op}$	1.3152	0.6187	1.3777	5.0065	90.0444***	70.8078	0.413	0.290	-8.6963***	186
$CSSD_{op}$	1.7379	0.8265	1.4729	5.4070	112.1528***	126.3872	0.439	0.379	-4.2822***	186
HSH_{op}	0.0015	0.1150	-0.0956	2.4631	2.5169	2.4483	0.977	0.954	-0.9526	186
$DHSH_{op}$	-0.0008	0.0222	0.8591	5.2463	61.6523***	0.0904	-0.020	-0.004	-14.2228***	185
$CSAD_{cl}$	2.8803	1.2518	1.6030	6.1559	156.8451***	289.8764	0.458	0.484	-4.7876***	186
$CSSD_{cl}$	4.0611	1.8201	1.7202	6.5177	187.6395***	612.8286	0.473	0.492	-4.7065***	186
HSH_{cl}	0.0011	0.0440	0.7299	3.8775	22.3613***	0.3554	0.782	0.610	-4.6685***	185

Table 6.8: Monthly correlation and Granger Causality tests: institutional herding measures and investor sentiment

SENT isUK market investor sentiment index; $SENT^p$is UK institutional investor sentiment; $CSAD_{op}$ is Cross Section Absolute Deviation of UK open-ended funds; $CSSD_{op}$ is Cross Section Standard Deviation of UK open-ended funds; HSH_{op} is the herding measure generated by Hwang and Salmon (2004) approach from UK open-ended funds; $DHSH_{op}$ is the first order of HSH_{op}; $CSAD_{cl}$ is Cross Section Absolute Deviation of UK closed-end funds; $CSSD_{cl}$ is Cross Section Standard Deviation of UK closed0end funds; HSH_{cl} is the herding measure generated by Hwang and Salmon (2004) approach from UK closed-end funds. AAII is American Association of Individual Investors index; II is Investors Intelligence index. The data cover the period 1st January 1996 to 30th June 2011.

Test 1: H_0: Granger-noncausality from herding measures to the sentiment indexes.
Test 2: H_0: Granger-noncausality from sentiment indexes to herding measures.

The tabulated statistics are the p-valus of the test statistics with 5 lags.
***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

Panel A: Correlation tests

	Open-ended funds			Closed-end funds		
	$CSAD_{op}$	$CSSD_{op}$	$DHSH_{op}$	$CSAD_{cl}$	$CSSD_{cl}$	HSH_{cl}
Variable	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
AAII	0.0036	0.0058	0.2239***	0.017	0.0177	-0.0993
II	-0.3169***	-0.2814***	0.1765**	-0.2739***	-0.2555***	0.0690
SENT	-0.2333***	-0.2021***	0.0682	-0.1477**	-0.1044	0.2429***
$SENT^p$	-0.5053***	-0.4924***	0.0912	-0.4375***	-0.4030***	0.1604**

Panel B: Granger Causality test

	$CSAD_{op}$		$CSSD_{op}$		$DHSH_{op}$		$CSAD_{cl}$		$CSSD_{cl}$		HSH_{cl}	
	Test 1	Test 2	Test 1	Test 2	Test 1	Test 2	Test 1	Test 2	Test 1	Test 2	Test 1	Test 2
AAII	0.3973	0.1221	0.3996	0.1725	0.0224	0.3493	0.4623	0.2204	0.4514	0.3259	0.7080	0.6475
II	0.6159	0.0007	0.7709	0.0062	0.1527	0.3140	0.8475	0.1157	0.7756	0.2621	0.8138	0.8974
SENT	0.208	0.7924	0.2309	0.9252	0.4470	0.4507	0.1955	0.6643	0.7828	0.2790	0.8575	0.5146
$SENT^p$	<0.0001	0.1347	<0.0001	0.3254	0.2800	0.8350	0.0001	0.2557	0.0007	0.4230	0.7718	0.9791

Regressions of beta herding suggest that both market sentiment and institutional sentiment has some power to explain open-ended funds herding, which is consistent with the results from weekly data. The estimated coefficients of closed-ended fund beta herding reveal a different story. The insignificant coefficients of sentiment variables suggest that UK institutional herding is affected neither by UK institutional sentiment nor UK market sentiment. Managers of open-ended fund are limited from arbitrageurs by the risk of large withdrawals if their performance is poor in the short-run (Stein, 2005) which puts them in danger to put on trades with attractive prospects in a long-run but the convergence to fundamentals may be not a rapid and smooth journey (Shleifer and Vishny, 1997).Managers of closed-end funds, however, are not constrained by such liquidity risk, which allows them to be able to enter in trades that are attractive in a long-run sense.

An examination of the impact from foreign investors' sentiment (represented by US investor sentiment) on UK institutional herding is also conducted in the monthly data. By including US sentiment variables and their lagged terms the model (model 1) is as follows:

$$H_t = \alpha + \sum_{j=1}^{3} \alpha_j H_{t-j} + \sum_{i=0}^{3} \beta_i SENT_{t-i} + \sum_{i=i}^{3} \gamma_i SENT_{t-i}^{p} + \sum_{i=0}^{3} \delta_i AAII_{t-i} + \sum_{i=0}^{3} \theta_i II_{t-i} + \varepsilon_t \tag{6.6}$$

whereH_t is the level of investor's herding behavior at time t, and it is measured by $CSAD$, $CSSD$,$DHSH_{op}$ or HSH_{cl} . $SENT$ is UK market sentiment, $SENT^p$ is UK institutional sentiment, $AAII$ is US individual sentiment and II is US institutional sentiment. The estimated parameters are presented in Table 6.10A and Table 6.10B. Some coefficients of the high order lagged term variables are highly insignificant; therefore, model 1 is amended by dropping some of the insignificant lagged terms to become model 2. The estimated parameters are also reported in Table 6.10A and 6.10B.

When open-ended fund herding is measured by return dispersions, $CSAD_{op}$or $CSSD_{op}$, Significant of $SENT_t^p$, II_{t-2} and II_{t-3} demonstrates that except current UK institutional sentiment, US institutional sentiment also affects UK institutional herding which is in two periods lagged and lasts for two periods. The insignificance of other coefficients implies that UK market sentiment and US individual sentiment have very little impact on institutional return herding. For $DHSH_{op}$measure, significant of coefficients of $SENT_t$, $SENT_{t-1}$, $SENT_t^p$, and $AAII_t$ suggests that not only UK market and institutional sentiment but also US individual sentiment has influence over open-ended funds beta herding. The estimates from monthly data are different from those of weekly data which indicate that the UK market sentiment and US individual sentiment has influence over open-ended funds return herding and US institutional sentiment affects open-ended funds beta herding. As explained above, this may because of the reverse effect in short run being eliminated in long-run.

Estimated coefficients of closed-end funds demonstrate that UK institutional sentiment, US individual and institutional sentiment have some power to explain the return herding and US institutional sentiment has an impact on closed-end funds beta herding. These results are, again, different from those of weekly data, which suggests that US institutional sentiment together with UK market and institutional sentiment influence the return herding. For beta herding, although the coefficient of II_{t-1} is significant in 10% level, both the value of the coefficient and the significant level indicate the effect from US institutional sentiment on closed-end funds beta herding is rather small. The insignificance of all other coefficients of sentiment variable implies that herding of closed-end funds on beta is unlikely to be caused by investor sentiment. This corresponds to the results of regression of weekly data.

As in the weekly analysis, institutional herding is examined in the different stages of financial crisis. The return and beta herding measures are separately regressed on SENT and $\mathrm{SENT}^{\mathrm{p}}$ under the conditions of non-crisis period, pre-crisis period, and in-crisis period. The model includes one lagged terms variable:

$$\begin{aligned} H_t = {} & \alpha_1^{no-cri} D_1 + \alpha_2^{no-cri} H_{t-1} * D_1 + \sum_{i=0}^{1} \beta_i^{no-cri} SENT_{t-i} * D_1 + \sum_{i=0}^{1} \gamma_i^{no-cri} SENT_{t-i}^{p} \\ & * D_1 + \alpha_1^{pre-cri} D_2 + \alpha_2^{pre-cri} H_{t-1} * D_2 + \sum_{i=0}^{1} \beta_i^{pre-cri} SENT_{t-i} * D_2 \\ & + \sum_{i=0}^{1} \gamma_i^{pre-cri} SENT_{t-i}^{p} * D_2 + \alpha_1^{in-cri} D_3 + \alpha_2^{in-cri} H_{t-1} * D_3 \\ & + \sum_{i=0}^{1} \beta_i^{in-cri} SENT_{t-i} * D_3 + \sum_{i=0}^{1} \gamma_i^{in-cri} SENT_{t-i}^{p} * D_3 + \varepsilon_t \end{aligned} \tag{6.7}$$

where the superscripts *nor-cri, pre-cri* and *in-cri* refer to no-crisis, pre-crisis and in crisis periods respectively; H_t is the institutional herding measures of $CSAD$, $CSSD$, or

$DHSH_{op}$ $(or\ HSH_{cl})$. $D_1 = 1$in non-crisis periods and zero otherwise; $D_2 = 1$ in pre-crisis periods and zero otherwise; $D_3 = 1$ for in-crisis periods and zero otherwiseThe regression results of open-ended funds and closed-end funds are displayed in Table 6.11A and Table 6.11B respectively.

The significant coefficients of γ_0^{no-cri} and $\gamma_0^{\mathrm{pre-cri}}$ from both $CSAD_{op}$ and $CSSD_{op}$ demonstrates that current institutional sentiment affects return herding of open-ended funds when the market is normal and in the pre-crisis period. Coefficients of UK market sentiment variables are statistically insignificant in all three stages, implying that UK market sentiment has hardly any impact on open-ended funds' return herding in all time. The tests of asymmetric effect of institutional sentiment on herding are rejected suggesting that the effect of institutional sentiment on return herding is symmetric during in all stages of the financial crisis. Return herding of closed-end funds (Tale 6.11B) demonstrates a similar picture: return herding is affected by institutional sentiment in the normal time and pre-crisis time. However, it is the lagged term rather than current institutional sentiment that has the effect, suggesting that institutional sentiment has one period delayed effect on return herding of closed-end funds. The significant of β^{in-cri}s suggests that market sentiment has some explanatory power over return herding of closed-end funds during financial crisis period. The estimates of $DHSH\ _{op}$show that beta herding of open-ended funds are affected by both market and institutional sentiment during normal time. It is affected by market sentiment during pre-crisis period and institutional sentiment in the crisis time. The beta herding of closed-ended funds, however, are not influenced by either market or institutional sentiment regardless the stage of financial sentiment.

Estimates of monthly data display some difference to those of weekly data. The effect of market sentiment on return herding significant in weekly estimations is insignificant in monthly estimations during normal time and pre-crisis period. The elimination of market sentiment effect in estimations of monthly data can be interpreted as the result of the 'second thought' effect in the short run, i.e. one week's sentiment effect is reversed in the following week (or weeks), the aggregate effect on herding from market sentiment in the long run is, therefore, not significant. During financial crisis, return herding of open-ended funds is unlikely to be affected by investor sentiment in monthly data which is influenced by both market and institutional sentiment in the weekly regression. This further suggests that investor sentiment effect on herding is in a short term rather than a long term. Beta herding estimations of open-ended funds demonstrate that only institutional sentiment has an impact to herding during normal time in the weekly data but both market and institutional sentiment have an impact in the monthly data, demonstrating that managers of open-ended funds are more likely influenced by market sentiment in a long run. This may because clients of open-ended funds normally assess fund performance, the return, in a relatively long run, mostly monthly or quarterly rather than in a short run such as daily or weekly. For closed-end funds, on the other hand, managers are less likely to be affected by market sentiment during normal and pre-crisis period in the long rung such as monthly, instead, they are influence by market sentiment in the short run such as weekly. This is confirmed by the estimates of beta herding of closed-end funds.

The possible asymmetric effect of investor sentiment under high and low UK market sentiment conditions is also examined in the monthly data. The market wide sentiment is defined as high when the sentiment at time t is higher than the mean, i.e. $SENT_t > \overline{SENT}$, where $\overline{SENT}$ is mean of the composted market sentiment. The market sentiment is defined as low when $SENT_t < \overline{SENT}$. Herding measures are regressed on the market sentiment, $SENT$, and the institutional sentiment, $SENT^p$ under high sentiment and low sentiment condition separately. The model is as follows:

$$H_t = \alpha_1^{high} D_1 + \alpha_2^{high} H_{t-1} * D_1 + \sum_{i=0}^{1} \beta_i^{high} SENT_{t-i} * D_1 + \sum_{i=0}^{1} \gamma_i^{high} SENT_{t-i}^p * D_1 + \alpha_1^{low} D_1 + \alpha_2^{low} H_{t-1} * D_2 + \sum_{i=0}^{1} \beta_i^{low} SENT_{t-i} * D_2 + \sum_{i=0}^{1} \gamma_i^{low} SENT_{t-i}^p * D_2 + \varepsilon_t \quad (6.8)$$

where the superscripts $high$ and low refer to high market sentiment and low market sentiment periods respectively; H_t is the herding measures of $CSAD$, $CSSD$, and $DHSH_{op}$ (or HSH_{cl}). $D_1 = 1$ when $SENT_t > \overline{SENT}$ and zero otherwise; $D_2 = 1$ when $SENT_t < \overline{SENT}$ and zero otherwise. The regression results are reported in Table 6.12.

The estimated coefficients demonstrate that institutional sentiment has a significant effect on institutional herding in terms of return and beta for both open-ended funds and closed-ended funds when market sentiment is high. However, the significant β_{t-1}^{high} for $DHSH_{op}$ demonstrates that open-ended fund beta herding is influenced by market sentiment rather than institutional sentiment in the high sentiment market. When market wide sentiment is low, institutional herding is generally not affected by investor sentiment, except closed-end fund return herding, which suggested that both market and institutional sentiment have an impact on beta herding of closed-end funds. Tests of asymmetric effect of investor sentiment on herding under high- and low-sentiment market suggest that effect of investor sentiment is symmetric under high or low market sentiment condition. This is different from the estimated results estimated from weekly data which indicate that there is an asymmetric effect of investor sentiment on return herding, which, again, corresponds to what CH suggested: that investor sentiment effect on returns is in a short run.

Table 6.9A: Monthly regression results of Open-ended funds herding on UK investor sentiment

Table 6.9A reports the results of regressions of the following general form:

$$H_t = \alpha_0 + \sum_{j=1}^{3} \alpha_j H_{t-j} + \sum_{i=0}^{3} \beta_i SENT_{t-i} + \sum_{i=0}^{3} \gamma_i SENT_{t-i}^{p} + \varepsilon_t$$

Variable definitions:

H= ***$CSAD_{op}$*, *$CSSD_{op}$* or $DHSH_{op}$**; so, $CSAD_{op}$ is Cross Section Absolute Deviation of UK open-ended funds; $CSSD_{op}$ is Cross Section Standard Deviation of UK open-ended funds; HSH_{op} is the herding measure generated by Hwang and Salmon (2004) approach from UK open-ended funds; $DHSH_{op}$ is the first order of HSH_{op}; **SENT**: UK market sentiment; **$SENT^P$**: UK institutional sentiment. **S.E**:Standard Error of regression; **AIC**: Akaike information criterion; **LM**: Breusch/Godfrey LM test for residual autocorrelation; **ARCH**: ARCH test for Heteroskadasticity. t-statistics are given in parentheses.

The model is estimated by using OLS with Newey-West HAC standard errors and covariance.The data cover the period 1st January 1996 to 30th June 2011.
***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

	$CSAD_{op}$		$CSSD_{op}$		$DHSH_{op}$	
	Model 1	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**
α_0	1.4750*** (4.7458)	1.6820*** (8.1982)	1.4611** (2.2854)	1.5585*** (3.0562)	-0.0045 (-0.9034)	-0.0049 (-1.1271)
α_1	0.1583* (1.9202)	0.1731** (2.1812)	0.1696* (1.7485)	0.1855* (1.8735)	-0.0771 (-1.2725)	-0.0983 (-1.3021)
α_2	-0.0132 (-0.1580)		0.1036 (0.8036)	0.0987 (0.8595)	-0.0522 (-0.6560)	
α_3	0.1255 (1.5084)		0.1562** (2.3119)	0.1317** (2.3814)	-0.0495 (-0.7216)	
$SENT_t$	-0.0060 (-0.8475)	-0.0008 (-0.1958)	-0.0059 (-0.6712)	0.0005 (0.0943)	0.0006** (2.0677)	0.0006** (2.3593)
$SENT_{t-1}$	0.0044 (0.4742)		0.0034 (0.2746)		-0.0003 (-0.7917)	-0.0005 (-1.3441)
$SENT_{t-2}$	0.0014 (0.1459)		0.0051 (0.3894)		-0.0005 (-1.4729)	-0.0003 (-1.2372)
$SENT_{t-3}$	0.0015 (0.2094)		0.0017 (0.1534)		0.00001 (-0.0370)	
$SENT^P{}_t$	-0.5715*** (-3.2672)	-0.5641*** (-4.6749)	-0.6529*** (-3.2646)	-0.5444*** (-2.8731)	0.0089* (1.7368)	0.0069* (1.6845)
$SENT^P{}_{t-1}$	0.0264 (0.1280)		0.0497 (0.1727)		-0.0027 (-0.3817)	
$SENT^P{}_{t-2}$	0.0335 (0.1641)		0.0022 (0.0098)		0.0050 (0.7349)	
$SENT^P{}_{t-3}$	-0.0204 (-0.1274)		0.0524 (0.2119)		-0.0050 (-0.7285)	
Adj. R^2	0.2449	0.2630	0.2704	0.2870	0.0158	0.0343
S.D.	0.5443	0.5336	0.7147	0.7028	0.0201	0.0210
AIC	1.6854	1.6032	2.2300	2.1645	-4.9127	-4.8585
LM	1.0713	1.1128	1.0561	0.9187	1.6334*	1.0669
ARCH	1.4294	2.1629	4.5731**	4.7744***	0.6432	1.9313

Table 6.9B: Monthly regression results of Closed-end funds herding on UK investor sentiment

Table 6.9B reports the results of regressions of the following general form:

$$H_t = \alpha_0 + \sum_{j=1}^{3} \alpha_j H_{t-j} + \sum_{i=0}^{3} \beta_i SENT_{t-i} + \sum_{i=0}^{3} \gamma_i SENT_{t-i}^{p} + \varepsilon_t$$

Variable definitions:

H= ***CSAD**$_{cl}$**, **CSSD**$_{cl}$* **or DHSH**$_{cl}$; so, CSAD$_{cl}$ is Cross Section Absolute Deviation of UK closed-end funds; CSSD$_{cl}$ is Cross Section Standard Deviation of UK closed-end funds; HSH$_{cl}$ is the herding measure generated by Hwang and Salmon (2004) approach from UK closed-end funds; **SENT**: UK market sentiment; **SENT^{P}**: UK institutional sentiment. **S.E**:Standard Error of regression; **AIC**: Akaike information criterion; **LM**: Breusch/Godfrey LM test for residual autocorrelation; **ARCH**: ARCH test for Heteroskadasticity. t-statistics are given in parentheses.

The model is estimated by using OLS with Newey-West HAC standard errors and covariance.The data cover the period 1st January 1996 to 30th June 2011.

***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

	CSAD$_{cl}$		CSSD$_{cl}$		HSH$_{cl}$	
	Model 1	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**
α_0	1.9194*** (3.0383)	1.8087*** (3.1284)	2.2652*** (2.9042)	2.2620*** (3.2334)	-0.0052 (-0.8082)	-0.0070 (-1.2286)
α_1	0.2113* (1.7623)	0.2318** (2.2062)	0.2211* (1.8801)	0.2570** (2.4725)	0.7662*** (9.9198)	0.7675*** (16.2116)
α_2	0.2770*** (3.3985)	0.3002*** (4.6790)	0.2834*** (3.5177)	0.3121*** (4.6919)	-0.0049 (-0.0508)	
α_3	0.0283 (0.3374)		0.0722 (0.8750)		0.0008 (0.0102)	
$SENT_t$	-0.0038 (-0.3177)	0.0051 (0.6114)	0.0007 (0.0417)	0.0110 (0.9440)	0.0003 (0.8067)	0.0003 (1.3381)
$SENT_{t-1}$	0.0216 (1.2577)		0.0252 (0.9791)		-0.0001 (-0.2669)	
$SENT_{t-2}$	-0.0187 (-0.9222)		-0.0227 (-0.8205)		0.0003 (0.6298)	
$SENT_{t-3}$	0.0098 (0.6384)		0.0141 (0.6687)		-0.0001 (-0.2614)	
$SENT^{P}_{t}$	-0.4050 (-1.4560)	-0.5522*** (-2.7537)	-0.5940 (-1.5454)	-0.7244*** (-2.7718)	0.0068 (0.8130)	0.0012 (0.2250)
$SENT^{P}_{t-1}$	-0.3040 (-0.8289)		-0.3272 (-0.5569)		-0.0081 (-0.7877)	
$SENT^{P}_{t-2}$	0.1143 (0.2812)		0.2637 (0.3909)		0.0021 (0.2095)	
$SENT^{P}_{t-3}$	-0.0899 (-0.2658)		-0.2124 (-0.4416)		-0.0026 (-0.3182)	
Adj. R^2	0.2947	0.3151	0.3059	0.3245	0.5956	0.6126
S.D.	1.0573	1.0396	1.5254	1.5020	0.0279	0.0274
AIC	3.0132	2.9423	3.7464	3.6783	-4.2562	-4.3337
LM	0.8569	0.8559	1.1708	1.2512	1.0026	0.6915
ARCH	3.1522**	3.9848**	4.0222**	3.9413**	1.6866	1.2024

Table 6.10A: Monthly regression results of open-ended herding on investor sentiment

Table 6.10A reports the results of regressions of the following general form:

$$H_t = \alpha_0 + \sum_{j=1}^{5} \alpha_j H_{t-j} + \sum_{i=0}^{5} \beta_i SENT_{t-i} + \sum_{i=0}^{5} \gamma_i SENT_{t-i}^{p} + \sum_{i=0}^{5} \delta_i AAII_{t-i} + \sum_{i=0}^{5} \theta_i II_{t-i} + \varepsilon_t$$

Variable definitions:

H= ***$CSAD_{op}$*, *$CSSD_{op}$* or $DHSH_{op}$**; so, $CSAD_{op}$ is Cross Section Absolute Deviation of UK open-ended funds; $CSSD_{op}$ is Cross Section Standard Deviation of UK open-ended funds; HSH_{op} is the herding measure generated by Hwang and Salmon (2004) approach from UK open-ended funds; $DHSH_{op}$ is the first order of HSH_{op}; **SENT**: UK market sentiment; **$SENT^P$**: UK institutional sentiment. AAII is American Association of Individual Investors index; II is Investors Intelligence index. t-statistics are given in parentheses.

The estimations are started from OLS method, if the Breusch-Godfrey Serial Correlation LM Test (including 2 lags) or ARCH test for Heteroskedasticity (including 1 lags) indicate that there is residual serial correlation and/or Heteroskedasticity in estimation, the method of Least Square with Newey-West HAC Standard Errors & Covariance is applied. The data cover the period 1st January 1996 to 30th June 2011.

***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

	$CSAD_{op}$		$CSSD_{op}$		$DHSH_{op}$	
	Model 1	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**
α_0	1.5170*** (2.9177)	1.6917*** (6.2568)	1.5159*** (3.9840)	1.6016*** (4.9780)	-0.00524 (-1.2466)	-0.0058 (-1.3340)
α_1	0.1714 (1.5580)	0.1787 (1.4126)	0.1801** (2.1701)	0.1853** (2.3248)	-0.07826 (-1.1251)	
α_2	-0.0346 (-0.3191)		0.0845 (1.0164)	0.0902 (1.1697)	-0.03146 (-0.3499)	
α_3	0.1194 (1.3988)		0.1483* (1.8023)	0.1286* (1.7762)	-0.01413 (-0.1910)	
$SENT_t$	0.0005 (0.0587)	0.0028 (0.6819)	0.0006 (0.0559)	0.0044 (0.7196)	0.00045 (1.5019)	0.0004* (1.6685)
$SENT_{t-1}$	-0.0026 (-0.2383)		-0.0048 (-0.3733)		-0.00045 (-1.2443)	-0.0007** (-2.5653)
$SENT_{t-2}$	0.0062 (0.6434)		0.0123 (0.9503		-0.00032 (-1.1060)	
$SENT_{t-3}$	0.0025 (0.3062)		0.0014 (0.1463)		-0.00004 (-0.1458)	
$SENT^P_t$	-0.4681*** (-2.7149)	-0.4596*** (-3.1935)	-0.5253*** (-2.2138)	-0.4295** (-2.4499)	0.00904* (1.8092)	0.0117* (1.8844)
$SENT^P_{t-1}$	-0.0523 (-0.2271)		-0.0199 (-0.0728)		-0.00256 (-0.3930)	-0.0068 (-1.1361)
$SENT^P_{t-2}$	0.0693 (0.3820)		0.0409 (0.1503)		0.00299 (0.4625)	
$SENT^P_{t-3}$	-0.0080 (-0.0461)		0.0608 (0.2823)		-0.00533 (-0.8287)	
$AAII_t$	0.0008 (0.2757)	0.0007 (0.2773)	0.0027 (0.7574)	0.0024 (0.7765)	0.00020** (2.3790)	0.0002*** (2.9697)
$AAII_{t-1}$	-0.0018 (-0.7977)		-0.0030 (-0.7983)		-0.00002 (-0.1636)	-0.0001 (-1.3486)
$AAII_{t-2}$	0.0007 (0.2423)		0.0025 (0.6797)		0.00002 (0.1768)	
$AAII_{t-3}$	-0.0006 (-0.2586)		-0.0013 (-0.3803)		-0.00014 (-1.3105)	
II_t	-0.0046 (-0.7732)	-0.0050 (-0.8677)	-0.0061 (-0.9410)	-0.0061 (-0.9868)	0.00004 (0.2740)	0.0001 (0.9343)
II_{t-1}	-0.0054 (-0.9824)	-0.0072 (-1.3427)	-0.0049 (-0.5914)	-0.0090 (-1.2542)	0.00008 (0.3923)	
II_{t-2}	0.0104 (1.6434)	0.0104** (2.0062)	0.0094 (1.1157)	0.0114* (1.6718)	0.00018 (0.7216)	
II_{t-3}	-0.0110* (-1.9117)	-0.0096** (-2.0708)	-0.0120* (-1.7187)	-0.0096* (-1.6900)	0.00001 (0.0300)	
Adj. R^2	0.2618	0.2894	0.2780	0.3010	0.0329	0.0816
S.D.	0.5382	0.5252	0.7109	0.6958	0.0199	0.0205
AIC	1.7026	1.5978	2.2594	2.1707	-4.8904	-4.8972
LM	0.9793	0.0755	0.9905	0.7930	3.8719**	0.6331
ARCH	2.8303*	4.5953**	1.6733	1.8477	0.3780	0.9868

Table 6.10B: Monthly regression results of closed-end herding on investor sentiment

Table 6.10B reports the results of regressions of the following general form:

$$H_t = \alpha_0 + \sum_{j=1}^{5} \alpha_j H_{t-j} + \sum_{i=0}^{5} \beta_i SENT_{t-i} + \sum_{i=0}^{5} \gamma_i SENT_{t-i}^{p} + \sum_{i=0}^{5} \delta_i AAII_{t-i} + \sum_{i=0}^{5} \theta_i II_{t-i} + \varepsilon_t$$

Variable definitions:
H= ***CSAD$_{cl}$*, *CSSD$_{cl}$*or DHSH$_{cl}$**; so, CSAD$_{cl}$ is Cross Section Absolute Deviation of UK closed-end funds; CSSDcl is Cross Section Standard Deviation of UK closed-end funds; HSHcl is the herding measure generated by Hwang and Salmon (2004) approach from UK closed-end funds;; **SENT**: UK market sentiment; **SENTP**: UK institutional sentiment. AAII is American Association of Individual Investors index; II is Investors Intelligence index. t-statistics are given in parentheses.**F1** is F-statistic for null of $\beta_0 = \gamma_0$. **F2** is F-statistic for null of $\delta_0 = \theta_0$.

The estimations are started from OLS method, if the Breusch-Godfrey Serial Correlation LM Test(including 2 lags) or ARCH test for Heteroskedasticity (including 1 lags) indicate that there is residual serial correlation and/or Heteroskedasticity in estimation, the method of Least Square with Newey-West HAC Standard Errors & Covariance is applied. The data cover the period 1st January 1996 to 30th June 2011.

***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

	CSAD$_{cl}$		CSSD$_{cl}$		HSH$_{cl}$	
	Model 1	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**
α_0	2.1866*** (3.0683)	2.0635*** (3.4066)	2.7109*** (3.1892)	2.6687*** (3.6899)	-0.0063 (-0.9694)	-0.0073 (-1.2815)
α_1	0.1895 (1.4989)	0.2015* (1.8796)	0.1861 (1.5185)	0.2243** (2.1033)	0.7605*** (9.6794)	0.7620*** (15.75)
α_2	0.2598*** (3.1161)	0.2868*** (4.3840)	0.2589*** (3.3003)	0.2941*** (4.4639)	-0.0180 (-0.1827)	
α_3	0.0197 (0.2413)		0.0718 (0.9464)		0.0004 (0.0054)	
$SENT_t$	0.0041 (0.3882)	0.0060 (0.7679)	0.0090 (0.5968)	0.0117 (0.9936)	0.0003 (0.7901)	0.0004 (1.5902)
$SENT_{t-1}$	0.0143 (0.8097)		0.0184 (0.6845)		-0.00002 (-0.0362)	
$SENT_{t-2}$	-0.0159 (-0.8583)		-0.0214 (-0.8371)		0.0003 (0.5850)	
$SENT_{t-3}$	0.0087 (0.5212)		0.0141 (0.6067)		0.00002 (0.0435)	
$SENT^P{}_t$	-0.3041 (-0.9896)	-0.4824** (-2.1814)	-0.5352 (-1.3834)	-0.6501** (-2.4268)	0.0084 (0.9443)	0.0029 (0.5146)
$SENT^P{}_{t-1}$	-0.3111 (-0.7960)		-0.3258 (-0.5207)		-0.0078 (-0.7391)	
$SENT^P{}_{t-2}$	0.2327 (0.5687)		0.5085 (0.7674)		0.0048 (0.4608)	
$SENT^P{}_{t-3}$	-0.1309 (-0.3798)		-0.2761 (-0.5455)		-0.0039 (-0.4643)	
$AAII_t$	0.0011 (0.2176)	0.0024 (0.5415)	-0.0025 (-0.3462)	0.0004 (0.0569)	-0.0002 (-1.2309)	-0.0002 (-1.4416)
$AAII_{t-1}$	0.0018 (0.3912)	0.00001 (0.0079)	0.0064 (0.9144)	0.0033 (0.5868)	0.0002 (1.1556)	0.0001 (1.12773)
$AAII_{t-2}$	0.0105* (1.9158)	0.0104*** (3.0325)	0.0142* (1.7911)	0.0146*** (2.9087)	-0.0002 (-1.2471)	
$AAII_{t-3}$	-0.0014 (-0.3056)		0.0015 (0.2301)		0.0001 (0.5874)	
II_t	-0.0178 (-1.3943)	-0.0194** (-2.2293)	-0.0235 (-1.2557)	-0.0264** (-2.0935)	0.0003 (1.0382)	0.0003 (1.1850)
II_{t-1}	-0.0055 (-0.4696)		-0.0081 (-0.4404)		-0.0004 (-1.2242)	-0.0005* (1.7785)
II_{t-2}	0.0026 (0.2108)		0.0016 (0.0854)		0.0002 (0.6229)	
II_{t-3}	-0.0050 (-0.3611)		-0.0084 (-0.4385)		-0.0004 (-1.4804)	
Adj. R^2	0.3134	0.3431	0.3247	0.3505	0.5929	0.6130
S.D.	1.0431	1.0181	1.5046	1.4727	0.0280	0.0274
AIC	3.0263	2.9215	3.7589	3.6598	-4.2096	-4.3135
LM	0.6587	0.2351	1.0085	1.2860	0.5502	0.0743
ARCH	6.4382**	9.2581***	5.1118**	6.3994**	1.6866	1.8541

Table 6.11A: Monthly regression open-ended funds herding on investor sentiment under financial crisis conditions

Table 6.11A reports the results of regressions of the following general form:

$$H_t = \alpha_1^{no-cri}D_1 + \alpha_2^{no-cri}H_{t-1} * D_1 + \sum_{i=0}^{1}\beta_i^{no-cri}SENT_{t-i} * D_1 + \sum_{i=0}^{1}\gamma_i^{no-cri}SENT_{t-i}^{p} * D_1 + \alpha_1^{pre-cri}D_2 + \alpha_2^{pre-cri}H_{t-1} * D_2 + \sum_{i=0}^{1}\beta_i^{pre-cri}SENT_{t-i} * D_2 + \sum_{i=0}^{1}\gamma_i^{pre-cri}SENT_{t-i}^{P} * D_2 + \alpha_1^{in-cri}D_3 + \alpha_2^{in-cri}H_{t-1} * D_3 + \sum_{i=0}^{1}\beta_i^{in-cri}SENT_{t-i} * D_3 + \sum_{i=0}^{1}\gamma_i^{in-cri}SENT_{t-i}^{p} * D_3 + \varepsilon_t$$

Variable definitions:
H= ***CSAD$_{op}$*, *CSSD$_{op}$* or DHSH$_{op}$**; so, CSAD$_{op}$ is Cross Section Absolute Deviation of UK open-ended funds; CSSD$_{op}$ is Cross Section Standard Deviation of UK open-ended funds; HSH$_{op}$ is the herding measure generated by Hwang and Salmon (2004) approach from UK open-ended funds; DHSH$_{op}$ is the first order of HSH$_{op}$; **SENT**: UK market sentiment; **SENT^{P}**: UK institutional sentiment. t-statistics are given in parentheses. $D_1 = 1$ in non-crisis periods and zero otherwise; $D_2 = 1$ in pre-crisis periods and zero otherwise; $D_3 = 1$ in in-crisis periods and zero otherwise. The pre- and in-crisis periods are as defined in Appendix 2. The no-crisis periods consist of the remaining observations in the sample. F1: f-statistical of hypothesis of $\beta_0 = \gamma_0$. F2 is f-statistic of null hypothesis of $\gamma_0^{no-cri} = \gamma_0^{pre-cri}$. F3 is f-statistic of null hypothesis of $\gamma_0^{pre-cri} = \gamma_0^{in-cri}$. F4 is f-statistic of null hypothesis of $|\gamma_0^{no-cri}| = |\gamma_0^{in-cri}|$.

The model is estimated by using OLS with Newey-West HAC standard errors and covariance. The data cover the period 1st January 1996 to 30th June 2011.
***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

	CSAD$_{op}$			**CSSD$_{op}$**			**DHSH$_{op}$**		
Coefficients	Normal period	pre-crisis period	in-crisis period	Normal period	pre-crisis period	in-crisis period	Normal period	pre-crisis period	in-crisis period
α$_1$	1.7081*** (6.3714)	2.4635*** (3.1789)	2.5775*** (4.1746)	2.2890*** (9.2776)	3.3635*** (3.4648)	3.4934*** (9.6772)	-0.0081 (-1.4348)	-0.0063 (-0.4657)	0.0242 (1.2287)
α$_2$	0.1087 (0.9514)	0.2859* (1.7327)	-0.1482 (-0.7639)	0.0696 (0.8448)	0.3506** (2.1324)	-0.1478 (-1.2898)	-0.1581* (-1.8275)	0.0128 (0.0935)	0.2466 (1.3422)
SENT$_t$	-0.0087 (-1.0122)	-0.0179 (-1.1167)	0.0050 (0.2422)	-0.0080 (-0.7529)	-0.0225 (-1.0989)	-0.0066 (-0.2670)	0.0005 (1.6043)	0.0015*** 3.7957	-0.0003 (-0.5387)
SENT$_{t-1}$	0.0021 (0.2357)	0.0070 (0.4592)	-0.0095 (-0.4917)	-0.0006 (-0.0500)	0.0058 (0.2418)	0.0023 (0.0831)	-0.0008** (-2.2648)	-0.0016*** (-3.3783)	0.0002 (0.3474)
SENT$^{P}_{t}$	-0.3864* (-1.7289)	-0.7377** (-1.9741)	-0.8645* (-1.9319)	-0.4430** (-2.2250)	-1.0559*** (-3.0110)	-0.8274 (-1.1776)	0.0205*** (3.0427)	0.0053 (0.7055)	-0.0400** (-2.0308)
SENT$^{P}_{t-1}$	-0.0938 (-0.4905)	-0.2755 (-0.6645)	-0.0041 (-0.0091)	-0.1984 (-0.8931)	-0.3723 (-0.7774)	-0.4135 (-0.6559)	-0.0078 (-0.8288)	-0.0025 (-0.2680)	0.0099 (0.5536)
F1	2.8057*	3.7481*	3.6603*	4.6111**	8.8453***	1.2869	8.6469***	0.2425	4.0908**
F2	0.6508			2.2887			2.2983		
F3	0.0473			0.0826			4.2650**		
F4	0.9135			0.2765			8.3739***		

Table 6.11B: Monthly regression closed-end funds herding on investor sentiment under financial crisis conditions

Table 6.11B reports the results of regressions of the following general form:

$$H_t = \alpha_1^{no-cri} D_1 + \alpha_2^{no-cri} H_{t-1} * D_1 + \sum_{i=0}^{1} \beta_i^{no-cri} SENT_{t-i} * D_1 + \sum_{i=0}^{1} \gamma_i^{no-cri} SENT_{t-i}^{p} * D_1 + \alpha_1^{pre-cri} D_2 + \alpha_2^{pre-cri} H_{t-1} * D_2 + \sum_{i=0}^{1} \beta_i^{pre-cri} SENT_{t-i} * D_2 + \sum_{i=0}^{1} \gamma_i^{pre-cri} SENT_{t-i}^{P} * D_2 + \alpha_1^{in-cri} D_3 + \alpha_2^{in-cri} H_{t-1} * D_3 + \sum_{i=0}^{1} \beta_i^{in-cri} SENT_{t-i} * D_3 + \sum_{i=0}^{1} \gamma_i^{in-cri} SENT_{t-i}^{p} * D_3 + \varepsilon_t$$

Variable definitions:
H= ***CSAD$_{cl}$*, *CSSD$_{cl}$* or DHSH$_{cl}$**; so, CSAD$_{cl}$ is Cross Section Absolute Deviation of UK closed-end funds; CSSD$_{cl}$ is Cross Section Standard Deviation of UK closed-end funds; HSH$_{cl}$ is the herding measure generated by Hwang and Salmon (2004) approach from UK closed-end funds; **SENT**: UK market sentiment; **SENT^{P}**: UK institutional sentiment. t-statistics are given in parentheses. $D_1 = 1$ in non-crisis periods and zero otherwise; $D_2 = 1$ in pre-crisis periods and zero otherwise; $D_3 = 1$ in in-crisis periods and zero otherwise. The pre- and in-crisis periods are as defined in Appendix 2. The no-crisis periods consist of the remaining observations in the sample. F1: f-statistical of hypothesis of $\beta_0 = \gamma_0$. F2: f-statistical of hypothesis of $\beta_1 = \gamma_1$. F3 is f-statistic of null hypothesis of $\gamma_1^{\text{no-cri}} = \gamma_1^{\text{pre-cri}}$. F4 is f-statistic of null hypothesis of $\gamma_1^{\text{pre-cri}} = \gamma_1^{\text{in-cri}}$. F5 is f-statistic of null hypothesis of $\gamma_0^{\text{no-cri}} = \gamma_0^{\text{in-cri}}$.

The model is estimated by using OLS with Newey-West HAC standard errors and covariance. The data cover the period 1st January 1996 to 30th June 2011.
***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

	CSAD$_{cl}$			CSSD$_{cl}$			HSH$_{cl}$		
Coefficients	Normal period	pre-crisis period	in-crisis period	Normal period	pre-crisis period	in-crisis period	Normal period	pre-crisis period	in-crisis period
α_1	4.3969*** (8.5815)	4.6233*** (3.6531)	2.0367** (2.3616)	5.9110*** (6.5582)	6.9264*** (3.7762)	2.1159** (2.0214)	-0.0078 (-1.1403)	-0.0195 (-0.7618)	0.0127 (0.6453)
α_2	-0.1041 (-1.2173)	0.4790*** (3.4702)	0.0492 (0.3048)	-0.0882 (-0.8451)	0.4516*** (3.4224)	0.0903 (0.5097)	0.7168*** (9.4628)	0.7923*** (9.4858)	0.8508*** (9.0277)
$SENT_t$	-0.0138 (-1.0689)	-0.0138 (-0.4697)	0.0154 (0.9225)	-0.0174 (-0.9867)	-0.0274 (-0.6848)	0.0600* (1.9414)	0.0005 (1.0786)	0.0006 (0.6674)	-0.0010 (-1.0947)
$SENT_{t-1}$	-0.0057 (-0.5075)	-0.0120 (-0.3070)	0.0834*** (2.6434)	-0.0105 (-0.6233)	-0.0093 (-0.1674)	0.1158** (2.0186)	-0.0004 (-1.0212)	0.0003 (0.2686)	0.0008 (0.8059)
$SENT^{P}_{t}$	-0.5406 (-1.3899)	0.0247 (0.0409)	-0.2887 (-0.6407)	-0.6715 (-1.2843)	0.2229 (0.2151)	-0.5522 (-0.7526)	0.0117 (1.0579)	0.0023 (0.1122)	0.0008 (0.0344)
$SENT^{P}_{t-1}$	-0.6012* (-1.8108)	-1.9030** (-2.9235)	-0.3833 (-0.8794)	-0.7939* (-1.7765)	-3.0201*** (-2.7698)	-0.4718 (-0.6643)	-0.0059 (-0.6713)	-0.0020 (-0.0718)	-0.0131 (-0.7423)
F1	-	-	-	-	-	0.6741	-	-	-
F2	3.1796*	8.8649***	1.0668	3.0106*	7.8409***	0.6263	0.378	0.0068	0.5817
F3	3.1573*			3.5615*			0.018		
F4	3.8203*			3.7658*			0.1288		
F5	0.1562			0.1469			0.1323		

Table 6.12: Monthly regression herding on investor sentiment indexes under market sentiment conditions

Table 6.12 reports the results of regressions of the following general form:

$$H_t = \alpha_1^{high} D_1 + \alpha_2^{high} H_{t-1} * D_1 + \sum_{i=0}^{1} \beta_i^{high} SENT_{t-i} * D_1 + \sum_{i=0}^{1} \gamma_i^{high} SENT_{t-i}^{p} * D_1 + \alpha_1^{low} D_1 + \alpha_2^{low} H_{t-1} * D_2 + \sum_{i=0}^{1} \beta_i^{low} SENT_{t-i} * D_2 + \sum_{i=0}^{1} \gamma_i^{low} SENT_{t-i}^{p} * D_2 + \varepsilon_t$$

Variable definitions:
H= ***CSAD, CSSD* or DHSH**; so, $CSAD_{op}$ is Cross Section Absolute Deviation of UK open-ended funds; $CSSD_{op}$ is Cross Section Standard Deviation of UK open-ended funds; HSH_{op} is the herding measure generated by Hwang and Salmon (2004) approach from UK open-ended funds; $DHSH_{op}$ is the first order of HSH_{op}; $CSAD_{cl}$ is Cross Section Absolute Deviation of UK closed-end funds; $CSSD_{cl}$ is Cross Section Standard Deviation of UK closed0end funds; HSH_{cl} is the herding measure generated by Hwang and Salmon (2004) approach from UK closed-end funds.**SENT**: UK market sentiment; **$SENT^P$**: UK institutional sentiment. t-statistics are given in parentheses. $D_1 = 1$when$SENT_t > \overline{SENT}$ and zero otherwise; $D_2 = 1$ when $SENT_t < \overline{SENT}$ and zero otherwise.**F1** is f-statistic of null hypothesis of $\beta_0 = \gamma_0$, F2 is f-statistic of null hypothesis of $\beta_1 = \gamma_1$. F3 is f-statistic of null hypothesis of $\alpha_1^{high} = \alpha_1^{low}$, where α_1^{high} is α_1 when $SENT_t > \overline{SENT}$ and α_1^{low} is α_1 when $SENT_t < \overline{SENT}$. F4 is f-statistic of null hypothesis of $\gamma_0^{high} = \gamma_0^{low}$, where γ_0^{high} is γ_0 when $SENT_t > \overline{SENT}$ and γ_0^{low} is γ_0 when $SENT_t < \overline{SENT}$. F5 is f-statistic of null hypothesis of $\beta_0^{high} = \beta_0^{low}$, where β_0^{high} is β_0 when $SENT_t > \overline{SENT}$ and β_0^{low} is β_0 when $SENT_t < \overline{SENT}$. . F6 is f-statistic of null hypothesis of $\beta_1^{high} = \beta_1^{low}$, where β_1^{high} is β_1 when $SENT_t > \overline{SENT}$ and β_1^{low} is β_1 when $SENT_t < \overline{SENT}$. SENTis UK market investor sentiment index; $SENT^p$ is UK institutional investor sentiment.

The model is estimated by using OLS with Newey-West HAC standard errors and covariance. The data cover the period 1st January 1996 to 30th June 2011.
***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

	Open-ended Funds						Closed-end Funds					
	$CSAD_{op}$		$CSSD_{op}$		$DHSH_{op}$		$CSAD_{cl}$		$CSSD_{cl}$		HSH_{cl}	
	High	Low	High	Low	High	Low	High	Low	High	Low	High	Low
α_1	2.3608*** (7.6108)	1.4832*** (4.6517)	3.0202*** (6.4995)	1.7931*** (4.0374)	0.0081 (0.6312)	-0.0088 (-1.5455)	2.7955*** (4.4019)	3.2871*** (3.4867)	3.7658*** (4.0902)	4.1168*** (2.9383)	-0.0037 (-0.2941)	-0.0073 (-1.0131
α_2	0.0037 (0.0291)	0.2740* (1.9253)	0.0793 (0.4859)	0.3162 (2.0225)	-0.1553 (-1.4916)	-0.0553 (-0.6508)	0.5180*** (3.9309)	0.2055 (1.0217)	0.5290*** (4.6702)	0.2686 (1.2969)	0.8648*** (16.1533)	0.5764*** (7.0828)
$SENT_t$	-0.0152 (-1.3374)	-0.0136 (-0.8642)	-0.0191 (-1.3848)	-0.0154 (-0.8571)	0.0005 (0.9220)	0.0007 (1.5828)	-0.0051 (-0.2633)	-0.0391* (-1.9649)	-0.0009 (-0.0339)	-0.0495** (-2.0062)	0.0001 (0.1627)	0.0001 (0.1824)
$SENT_{t-1}$	0.0088 (0.8184)	0.0014 (0.1160)	0.0098 (0.7144)	0.0028 (0.1833)	-0.0009** (-2.5315)	-0.0006 (-1.6222)	-0.0003 (-0.0146)	0.0255 (1.4464)	-0.0032 (-0.1162)	0.0362 (1.3054)	-0.0002 (-0.5090)	0.0003 (0.5597)
$SENT^P_t$	-0.6878*** (-3.9490)	-0.3659 (-1.2918)	-0.7844*** (-3.0385)	-0.3982 (-1.1905)	0.0147 (1.3258)	0.0084 (1.1544)	-0.6559* (-1.7213)	-0.2406 (-0.4967)	-1.1047* (-1.8486)	-0.1608 (-0.2224)	0.0187* (1.6683)	0.0062 (0.4555)
$SENT^P_{t-1}$	-0.1105 (-0.7697)	-0.0267 (-0.1175)	-0.2589 (-1.1077)	-0.0899 (-0.3333)	-0.0147 (-1.2743)	-0.0018 (-0.2608)	-0.3906 (-1.0184)	-0.6933* (-1.9743)	-0.3179 (-0.5209)	-1.0110** (-1.9989)	-0.0100 (-0.7936)	-0.0098 (-1.0969)
F1	14.8360***	1.4368	9.0338***	1.2265	-	1.0530	2.9228*	0.1709	3.3906*	0.0237	2.7760*	0.1823
F2	-	-	-	-	1.4456	-	1.0123	4.0141**	0.2585	4.0851**	0.6049	1.2078
F3	4.1607**		4.4886**		-		0.2097		0.0457		-	
F4	0.9211		0.8022		-		0.4453		0.9548		0.5314	
F5	-		-		-		1.5335		1.7392		-	
F6	-		-		0.2375		-		-		-	

6.3 Conclusion

In this chapter, the interest of research is the relationship between institutional herding and investor sentiment, particularly, the effects of investor sentiment on institutional herding. The analysis examines herding measure which is defined as return herding (represented by CSAD and CSSD) and beta herding, HSH, against domestic, $SENT$ and $SENT^p$, and foreign investor sentiment measures, AAII and II. This process is conducted by using UK open-ended funds and closed-end funds as test samples and exploring how sentiment of different groups of investors influences institutional investor herd behaviour. Weekly and monthly data are used to examine sentiment effects on herding in different frequency data. The similar estimation results from different frequency data demonstrate the consistence of sentiment effect on herding behaviour. Estimation differences, however, suggests that factors which influence institutional herding vary in different investment intervals.

The investor sentiment effect on institutional herding is firstly investigated by using weekly data. Regressions reveal that investor sentiment, in general, contributes to institutional investor herd behaviour, more especially, institutional sentiment has an important role in herding. When considering foreign investor sentiment (represented by US investor sentiment) in the analysis, it shows that US investor sentiment also has significant influence on the UK institutional herding. However, the significance of foreign sentiment effect is to a greater level in open-ended funds than that in closed-end funds. This difference demonstrates that managers of open-ended funds are more likely to be affected by a wider range of investor sentiment because investor flows cause liquidity-motivated trading of open-ended funds.

The impact on UK institutional herding from different groups of investors is also examined in the different stages of financial crisis. Both market and institutional sentiment have some impact on institutional herding in normal times. Market sentiment tends to have a reverse effect on herding, i.e. one week's effect is reversed in the following week (or weeks).

In pre-crisis periods, only market sentiment has explanatory power to the institutional herding. However, institutional sentiment also plays a role in open-ended funds' return herd behaviour. During financial crisis periods, both market and institutional sentiment have a delayed effect on institutional herding. However, the beta dispersion measure shows that institutional herding in financial crisis periods has no relation to investor sentiment. This may suggest that the bias of fund managers' risk-return relation is caused by other factors rather than investor sentiment.

The investor sentiment effect on institutional herding is examined under different market sentiment condition. There is an asymmetric sentiment effect on return herding, but sentiment effect on beta herding is symmetric under high- or low-market-sentiment conditions.

The examination using monthly data confirms that both UK and US investor sentiment have an impact on UK institutional herding suggested by weekly analysis. However, the UK market sentiment is not significant in the monthly estimation which may because of the reverse effect in the weekly data. The market sentiment effect on herding in one week is reversed in the following week (weeks), suggesting that the sentiment effect in the short run is eliminated in the long-run. The estimated coefficients also indicate that institutional sentiment influence is more significant in the short investment interval (weekly) than that in the long investment interval (monthly). However, this is not always the case when herding is measured by the dispersion of CAPM betas, which suggest that the institutional sentiment and individual sentiment may have the same degree of impact on beta herding in the monthly interval.

Estimates of monthly data by examining sentiment effect on herding in different stages of financial crisis display some differences to those of weekly data. The effect of market sentiment on return herding is not significant in monthly estimations during normal time and pre-crisis period. The elimination of market sentiment effect in estimations of monthly data can be interpreted as the result of the reverse effect in the short run. During financial crisis, return herding of open-ended funds is unlikely to be affected by investor sentiment in monthly data. This further suggests that investor sentiment effect on herding is in a short term rather than a long term. Beta herding estimations of open-ended funds demonstrate that only institutional sentiment has an impact to herding during normal time in the weekly data but both market and institutional sentiment have impact in the monthly data, suggesting that managers of open-ended funds are more likely influenced by market sentiment in a long run.

The estimated coefficients demonstrate that institutional sentiment has significant effect on institutional herding in terms of return and beta in the high sentiment market, but investor sentiment generally has no effect on institutional herding when market wide sentiment is low in the monthly estimation. Tests of asymmetric effect of investor sentiment under high- and low-sentiment market suggest that it is symmetric. This is different from the estimated results from weekly data which indicate that there is an asymmetric effect of investor sentiment on return herding, which, again, corresponds to what CH suggested: that investor sentiment effect on returns is in a short run.

The contributions of the chapter are: firstly, it is the first attempt to examine the relation between investor sentiment and investor herding directly by using the measures generated in previous studies; secondly, a comprehensive study of herding source of UK open-ended and closed-end funds is conducted in the chapter and the similarities and differences of the investor sentiment effects are revealed; finally, the study also investigates the sentiment effect on institutional herding under different market conditions, and finds that different measures of institutional herding can lead to quite different results.

Chapter 7 Conclusion and Future Work

Recent studies shed important light on a range of issues regarding investor sentiment and behaviour: the impact that investor sentiment has on asset prices; how sentiment of different groups of investors influence asset pricing; how far investor sentiment is contagious across borders; how institutional investors herd in the market; and whether institutional herding is caused by investor sentiment.

The content in this thesis is a further step in analysing investor sentiment as well as investor herd behaviour and focuses on the UK financial market. Section 7.1 is a summary and the key findings of the study. Section 7.2 points out the limitations of the thesis and proposes the directions for future research.

7.1 **Summary and the key findings**

The objectives of this thesis are threefold. First, using weekly and monthly financial data, the impact of investor sentiment in UK financial markets in different investment intervals is investigated. This is conducted by constructing measures of sentiment for the UK investors and examining how far sentiment in one country (focussing on the UK) is caused by sentiment in the others (the US and Germany), or vice-versa. The impact of investor sentiment in the UK, US and Germany on UK asset returns is further studied, including distinguishing between 'tranquil' market periods and periods of financial crisis. Three key results are found: i) UK sentiment is Granger-caused by US individual and institutional sentiment but not the reverse; ii) when US and UK sentiment are included in the same regression, UK equity returns are significantly influenced by US individual and institutional sentiment and hardly at all by local UK investor sentiment. In other words, our results suggest that UK investor sentiment is "made in the USA". iii) The sentiment contagion across borders is more pronounced in the shorter investment interval (i.e. weekly interval).

Second, the thesis investigates herd behaviour, particularly institutional herding by studying UK mutual fund data. The investigation is conducted by examining return dispersions of UK mutual funds in daily, weekly and monthly intervals. Two categories of mutual funds (UK open-ended and UK closed-end) are collected for the investigation of institutional herding behaviour. UK open-end funds concentrate on UK equity focused funds, and closed-end funds are not limited by asset allocation.

Return dispersion methods proposed by CH and CCK are used to detect herding behaviour of UK institutional investors. Little evidence of herding in return dispersion measures is found, i.e. a lower level return dispersion during market stress time or a trend of reducing dispersion among increasing market return has not been found. This is consistent for both open-ended and closed-end funds. However, when market stress period is defined as financial crisis in CH method, return herding is found in the daily and weekly investment intervals during the pre-crisis period.

Beta dispersion method introduced by HS is also utilised in the study. It suggests that herd behaviour is more likely to be persistent and to affect CAPM betas of portfolios. Strong evidence of herding among fund managers in CAPM beta is found, and this is consistent in both open-ended and closed-end funds. The study also demonstrates that beta herding is not caused by market fundamental and macroeconomic factors, instead, it perhaps arises from investor sentiment.

Finally, the causal relation between institutional herding and investor sentiment is explored. This is conducted by directly examining the measures of institutional herding against the measures of investor sentiment in UK and US. The key results that have been found in this part of study are: i) investigations of both return herding and beta herding suggest that UK institutional herding is generally influenced by investor sentiment. When taking US investor sentiment into account, the investigation shows that US investor sentiment also has significant influence on the UK institutional herding. ii) Sentiment of different groups of investors affect institutional herding in a different degree and it depends on the forms of the fund particular in weekly investment interval. Open-end fund managers are more likely to be affected by individual investor sentiment, whereas closed-end fund managers herd on institutional sentiment. iii) The investigation of sentiment effect on UK institutional herding in different stages of financial crisis suggests investor sentiment has a significant effect on return herding behaviour in all stages of financial crisis, but has no significant effect on beta herding during financial crisis in the weekly interval.

The main contribution of this thesis is that practical investor sentiment indices are constructed to measure UK market wide investor sentiment and UK institutional investor.

Prior literature and available sentiment indices focus on the United States: very few sentiment indices have been constructed for UK investor sentiment. The only two, to the author's knowledge, are an annual market-wide index by Baker et al (2012), and a weekly market-wide index by Bai (2014) based on the Baker and Wurgler (2006) approach.The UK market wide investor sentiment composed in this study, although not the first, it is a more comprehensive one. Combining the approaches of Brown and Cliff (2004) and Baker and Wurger (2006), the index is constructed by including a wider range of investor sentiment proxies and at both weekly and monthly frequencies. Moreover, the UK institutional sentiment index is one of the very few composed indices which measure institutional investor sentiment and it is the first such for the UK.

The second contribution of the thesis is that the composed UK investor sentiment measures are examined against the US, German investor sentiment measures and it reveals that the UK investor sentiment is heavily influenced by US and German investor sentiment. US individual and institutional sentiment, and German sentiment all have the power to predict UK market sentiment, and US institutional sentiment has a greater effect on UK market sentiment than US individual sentiment has. UK institutional sentiment, on the other hand co-moves with the US investor sentiment, and it is also affected by German investor sentiment.

The third contribution of this thesis is the investigation of the impact of investor sentiment on asset returns with size effect. Specifically, we examine the sentiment impact across different financial crisis stages, which demonstrate that price bubble, to some degree, is caused by investor sentiment, and financial crisis is normally a process of price reversal back to the fundamental. Moreover, the impact of foreign investor sentiment on UK equity returns is studied, as a large proportion of UK equities are held by foreign investors, and we find that UK equity returns are influenced heavily by US individual and institutional sentiment and hardly at all by local investor sentiment.

The fourth contribution of the thesis is the attempt to examine institutional herding on a cross-section basis. The previous studies of institutional herding focus on examining whether the individual stock has been bought or sold by a number of financial institutions at the same time. The methods developed by CH, CCK and HS are applied for the first time to study institutional herding. CH and CCK approaches are used to examine herding behaviour of portfolio returns and HS approach investigates herding behaviour of portfolio betas. The study also examines two different groups of UK mutual funds, open-ended and closed-end fund, for institutional herding behaviour, which is the first attempt of comparing herding behaviour of these two categories funds.

The fifth contribution of the thesis is to explore the relation between investor sentiment and investor herding by directly examining the measures of institutional herding along with investor sentiment measures. This is the first attempt to examine the causal relation of investor sentiment to institutional herding by building models which use sentiment measures as explanatory variables.

7.2 Limitations and Directions for Future Research

A number of limitations in this study and a future research area as follow.

The first limitation of the thesis perhaps involves the component sentiment variables that are used for constructing UK sentiment indexes. Eight sentiment indicators were used in the study, but this did not include variables such as the number of IPOs and the first day return of IPOs which are used in the Baker & Wurgler (2006) approach. These are not very suitable weekly frequency data. The absence of direct survey data on investor sentiment in UK financial markets leads to the difficulty of checking the validity of the constructed indexes. This provides one of the future research areas that identify further sentiment indicators which are suitable for weekly or even higher frequencies to construct better measures for investor sentiment.

The second limitation of the thesis relates to the methodology of detecting herd behaviour in the market. In the study, institutional herding was investigated by utilizing Christie and Huang (1995), Chang, Cheng, and Khorana (2000), and Hwang & Salmon (2004) methods. The former two approaches reveal the herd behaviour by examining the relation between return dispersion and market returns and the latter is to discover herding by examining CAPM Beta dispersion. As discussed in the study, each of the methods has its drawbacks. Although, alternative methods are introduced to overcome them, there still more could be done. For example, to define a better criterion for market stress in Christie and Huang (1995) approach. Moreover, in contrast to Hwang & Salmon (2004)'s CAPM Beta bias, Jensen's Alpha (Jensen, 1967) of mutual funds may also reveal the fund managers herd behaviour.

The third limitation of the thesis relates to the number of UK open-end mutual funds used for studying institutional herd behaviour. Research on a mature market usually prefers a much larger sample of data; however, it is difficult to expand the data without shortening the examination time period. Since the methods of studying institutional herding are time-series analysis, sacrifice on the number of sample funds is better than length of sample period. This, on the other hand provides another possible empirical study opportunity. Investment funds include hedge fund, mutual funds, and pension funds. UK mutual funds are studied in the thesis as a sample of institutional herding, but the investigation of herd behaviour on UK hedge funds and pension funds is still absent. Therefore, a study of other classes of UK investment fund can be further research to prove institutional herd behaviour.

Moreover, this thesis focuses on sentiment effects on UK equity pricing. The reverse relation is already hinted in some tests in the thesis. This research may be able to shed light on how investor sentiment is contagious across borders. The study suggests that US investor sentiment has a significant effect on UK equity returns, and the UK investor sentiment that affects return, is in fact “Made in USA”. Will this actually transfer through to the return of asset, as the US investors hold a significant proportion of the UK equities?

Appendix 1: List of UK Open-ended Funds

ABERDEEN UK MID CAP A INC.	L&G.UK INDEX RET.DIS.
AEGON UK EQUITY A GBP	L&G.N UK GROWTH AC.
ALLIANZ RCM UK GROWTH	LEGG MASON UK EQUITY A
ALLIANZ RCM UK MID CAP	LIONTRUST UK GROWTH
ALLIANZ RCM UK INDEX A ACCUMULATION	LIONTRUST TOP 100 R
ARTEMIS UK SPECIAL SITUATIONS	M&G UK GROWTH A AC.
AEGON ETHICAL EQUITY A	M&G UK SELECT A INC GBP
AXA FRAMLINGTON UK SELECT OPPS.INC	M&G SECS.UK.GW.INC.
AXA FRAM.UK GW.INC.	M&G SECS.REC.FD.AC.
BAILLIE GIFF UK EQUITY ALPHA C INC.	M &.G RECOVERY A INC.
BAILLIE GIFF UK EQUITY ALPHA B INC.	MARKS & SPENCER UK SEL. PTF INC.
BAILLIE GIFF UK EQUITY ALPHA A INC.	MARKS &.SPEN.UK 100 COS. AC.
BARING UK GROWTH	NEWTON INCOME SIS
BLACKROCK UK EQUITY INC.	OLD MUT.UK SLT.EQ.INC.
BLACKROCK UK SPECIAL SITUATIONS INC.	PREMIER UK ALPHA GROWTH R INC.
BLACKROCK UK INC.	PREMIER ETHICAL R INC.
CAZENOVE UK OPPS.A AC.	PREMIER UK MID 250 RET
CF CANLIFE GW.	PRU.UK GROWTH A INC.
CIS UK GROWTH	RATHBONE RECOVERY INC.
CIS.SUSTAINABLE LEADERS TRUST	RYL.BK.SCTL.GW.FD.
ECCLESIASTICAL AMITY UK A	RELIANCE BRITISH LIFE
ECCLESIASTICAL AMITY C	RENSBURG UK BLCHP.GW. TRUST
F&C UK ALPHA SC1 AC.	ROYAL LONDON UK GROWTH A
F&C STEWARDSHIP GROWTH SC1 INC	SANTANDER UK GROWTH INC.
FAMILY CHARITIES ETHICAL INC.	SANTANDER N &.P UK GW.
FAMILY ASSET	SCHRODER UK EQUITY A INC.
FIDELITY SPECIAL SITUATIONS AC.	SCOT.MUT.UK EQUITY INC.
HSBC FTSE 100 IDX.RET.INC.	SCWID.UK SLT.GW.CL.A AC.
HSBC FTSE 100 INDEX AC. RETAIL	SCWID.UK SLT.GW.RET.C AC.
IGNIS BALANCED GROWTH INC.	SCWID.UK GW.A
INVESCO PERP.CHILDREN'S	SCWID.UK TRKR.RET.A INC.
INVESCO PERP.UK GW.INC.	STANDARD LIFE TM.UK EQ. GENERAL INC.
INVESTEC UK SPECIAL SITUATIONS A INC.	SMITH & WILLIAMSON UK EQUITY GROWTH
INVESTEC UK ALP.A NET AC.	SJP UK & GENERAL PROGRESSIVE INC.
INVESTEC UK SM.COS.A NET ACC	SWIP UK OPPORTUNITIES A
JPM PREMIER EQUITY GROWTH A ACC	THORNHILL CAPITAL
JUPITER UK GROWTH INC.	THREADNEEDLE UK INSTL.2
L&G.BCLYS 500 DIST.	THREADNEEDLE UK SLT.1
L&G.EQUITY E AC.	THREADNEEDLE UK GW.& INC.1
L&G.EQUITY E DIS.	THREADNEEDLE UK OVERSEAS EARNS.2
L&G.UK ACTIVE OPPS.E DIS.	TU BRITISH
L&G.UK 100 INDEX E AC.	VIRGIN UK INDEX TRACKING

Appendix 2: List of UK Closed-end Funds

3I GROUP	GRAPHITE ENTERPRISE TST.
ABDN.SMCOS.HI.INC.TST.	GRESHAM HOUSE
ABERDEEN ASIAN SMCOS.	HANSA TRUST
ABERDEEN NEW DAWN IT.	HANSA TRUST 'A'
ABERDEEN NEW THAI	HEND.EUROTR.ORD.
ABERFORTH SMCOS.	HENDERSON ASIAN GW.TST.
ALBANY INV.TRUST	HENDERSON EUR.FOCUS TST.
ALLIANCE TRUST	HENDERSON FAR EAST INC.
BAILLIE GIFF.JAPAN	HENDERSON FLEDGLING TST.
BAILLIE GIFF.SHIN NIPPON	HENDERSON GLB.TST.
BANKERS INV.TRUST	HENDERSON OPPS.TRUST
BARONSMEAD VCT	HENDERSON PRIV.EQ.IT.
BLACKROCK LNAMER.IT.	HENDERSON SMALLER COS.
BLACKROCK SMCOS.TST.	HERALD INV.TST.
BLACKROCK WORLD MNG.	HG CAPITAL TRUST
BRITISH & AMERICAN IT.	INTL.BIOTECHNOLOGY
BRITISH ASSETS	INVESCO ASIA TRUST
BRITISH EMPIRE SECS.	INVESCO PERP.UK SMCOS.
BRUNNER INV.TST.	JPMORGAN AMERICAN IT.
CANDOVER INVS.	JPMORGAN CHINESE
CAPITAL GEARING TST.	JPMORGAN CLAVERHOUSE
CAYENNE TRUST	JPMORGAN EMRG.MKTS.
CITY NATRES.HI.YLD.TST.	JPMORGAN EUR.SMALL CO.
CITY OF LONDON IT.	JPMORGAN EUROPEAN IT.
DUNEDIN ENTERPRISE	JPMORGAN INDIAN IT.
DUNEDIN INC.GROWTH	JPMORGAN JAP.SMCOS.TST.
DUNEDIN SMALLER COS.	JPMORGAN JAPANESE
EASTERN EUROPEAN TRUST	JPMORGAN MID CAP IT.
EDINBURGH DRAGON TST.	JPMORGAN OVERSEAS IT.
EDINBURGH INV.TRUST	JPMORGAN SMALLER COS.
EDINBURGH UK TRACKER	JPMORGAN US SMALLER COS.
ELECTRA PRIVATE EQUITY	JUPITER PRIMADONA GROWTH
EUROPEAN ASSETS TST.	KEYSTONE IT.
F&C CAPITAL & INCOME	LAW DEBENTURE
F&C GLOBAL SMALLER COS.	LLOYDS SMCOS.CAPITAL DELISTED
F&C US.SMALLER COS.	LONDON & ST.LAWRENCE
FIDELITY EUR.VALUES	LOWLAND INV.
FIDELITY JAPANESE VALUES	MAJEDIE INVS.
FIDELITY SPC.VALUES	MARTIN CURRIE PACIFIC
FINSBURY GW.& INC.TST.	MERCANTILE IT.
FOREIGN & COLONIAL	MERCHANTS TRUST
GENESIS EMRG.MKTS.	MID WYND INTL.IT.

List of UK Closed-end Funds (continue)

MITHRAS INV.TST.	WITAN INV.TRUST
MONKS INV.TRUST	WITAN PACIFIC IT.
MONTANARO EUR.SMCOS.TST	WORLD TRUST FUND
MONTANARO UK SMCOS.IT.	WORLDWIDE HLTHCR.TST.
MURRAY INCOME	
MURRAY INTL.	
MURRAY INTL.'B'	
NEW CITY HIGH YIELD FD.	
NEW INDIA IT.	
NORTH AMERICAN INC.TST.	
NORTH ATLANTIC SMCOS.	
NORTHERN INVESTORS CO.	
NORTHERN VENTURE TST.	
PACIFIC ASSETS	
PACIFIC HORIZON	
PANTHEON INTL.PARTS.	
PERSONAL ASSETS	
RCM TECHNOLOGY TRUST	
RIGHTS & ISSUES CAP.	
RIT CAPITAL PARTNERS	
SCHRODER ASIA PAC.FD.	
SCHRODER INCOME GW.FD.	
SCHRODER JAPAN GW.FD.	
SCHRODER UK GROWTH FD.	
SCHRODER UK MID CAP.FD.	
SCOTTISH AMERICAN	
SCOTTISH INV.TST.	
SCOTTISH MORTGAGE	
SCOTTISH ORIENTAL SMCOS.	
SHIRES INCOME	
STANDARD LIFE UK SM.COS.	
STD.LIFE EQUITY INC.TST.	
SVM GLOBAL FUND	
TEMPLE BAR	
TEMPLETON EMRG.MKTS.IT.	
THE EUROPEAN IT.	
THROGMORTON TRUST	
TR EUROPEAN GROWTH	
TR PROPERTY INV.	
TROY INCOME & GW.TST.	
UK SELECT TRUST	
VALUE AND INC.TST.	

Appendix 3 Results for regressions without contemporaneous variables

Table A1: Weekly regressions of returns on sentiment proxies

Table A1 shows the results of estimating equations of the following form:

$$R_{size} = \alpha_0 + \sum_{i=1}^{2} \beta_{1,i} AVDC_{t-i} + \sum_{i=1}^{2} \beta_{2,i} CEFD_{t-i} + \sum_{i=1}^{2} \beta_{3,i} MFI_{t-i} + \sum_{i=1}^{2} \beta_{4,i} PCV_{t-i} + \sum_{i=1}^{2} \beta_{5,i} PCO_{t-i} + \sum_{i=1}^{2} \beta_{6,i} RSI_{t-i} + \sum_{i=1}^{2} \beta_{7,i} VOLA_{t-i} + \sum_{i=0}^{2} \beta_{8,i} DVAR_{t-i} + \varepsilon_t$$

As there is some evidence of autocorrelation, the estimation method is OLS with Newey-West standard errors.

Variable definitions:
size = *big*, *mid* or *sml*; so, $\boldsymbol{R_{big}}$: return on the large-size stock portfolio; $\boldsymbol{R_{mid}}$: return on mid-size stock portfolio; $\boldsymbol{R_{small}}$: return on small-size stock portfolio; **AVDC**: Advances to declines ratio; **CEFD**: Closed-end Fund Discount; **MFI**: Money Flow Index; **PCV**: Put-call volume ratio; **PCO**: Put-call open interest ratio; **RSI**: Relative Strength Index; **VOLA**: Realized volatility; **DVRA**: first difference of Trading volume. ***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

	R_{big}		R_{mid}		R_{sml}	
Variable	**Coefficient**	**t-Statistic**	**Coefficient**	**t-Statistic**	**Coefficient**	**t-Statistic**
$AVDC_{t-1}$	-0.5128**	-2.2193	-0.1572	-0.7172	0.7900***	4.6034
$AVDC_{t-2}$	-0.0645	-0.3071	0.0284	0.1086	0.3942*	1.8778
$CEFD_{t-1}$	0.1245	0.5640	0.5084**	2.3354	0.4485***	3.1522
$CEFD_{t-2}$	-0.0881	-0.4160	-0.3455**	-1.7865	-0.2630**	-2.0019
MFI_{t-1}	0.0025	0.4101	0.0047	0.7163	0.0106*	1.8744
MFI_{t-2}	-0.0057	-0.8975	-0.0032	-0.4970	-0.0055	-1.0795
PCV_{t-1}	-0.1799	-0.8118	0.0862	0.4679	0.2177	1.5059
PCV_{t-2}	0.1677	0.8137	-0.0387	-0.2300	0.0130	0.0970
PCO_{t-1}	2.4341	1.3562	1.7221	1.1018	1.4706	1.1632
PCO_{t-2}	-2.2657	-1.2815	-2.3377	-1.5175	-2.4847**	-2.0485
RSI_{t-1}	0.0026	0.5744	0.0055	1.1527	0.0057	1.4528
RSI_{t-2}	-0.0002	-0.0385	-0.0014	-0.2893	-0.0007	-0.1823
$VOLA_{t-1}$	-0.7398	-1.4502	-1.0458**	-2.3020	-0.7660**	-2.5083
$VOLA_{t-2}$	0.6791	1.5732	0.5088	1.5378	0.1476	0.5559
$DVAR_{t-1}$	-0.7779	-0.5026	-1.3572	-0.8130	-0.7044	-0.4815
$DVAR_{t-2}$	3.2671**	2.1243	5.0027***	3.3418	3.8999***	3.1153

Table A2: Regression of weekly returns on UK sentiment indexes

Table A2 reports the results of regressions of the following general form:

$$R_{size,t} = \alpha_0 + \sum_{j=1}^{4} \alpha_j R_{size,t-j} + \sum_{i=0}^{4} \beta_i SENT_{t-i} + \sum_{i=0}^{4} \gamma_i SENT_{t-i}^{p} + \varepsilon_t$$

The data are weekly and cover the period 1st January 1996 to 30th June 2011. Exceptionally the *SENTIX* index is available only from 28th February 2001. The estimation method is OLS with Newey-West standard errors.

Variable definitions:

size = *big*, *mid* or *sml*; so, $\boldsymbol{R_{big}}$: return on the large-size stock portfolio; $\boldsymbol{R_{mid}}$: return on mid-size stock portfolio; $\boldsymbol{R_{small}}$: return on small-size stock portfolio; **SENT**: UK market sentiment; $\mathbf{SENT^P}$: UK institutional sentiment.

$\bar{\mathbf{R}}^2$: the Adjusted R-squared; **S.E**:Standard Error of regression; **AIC**: Akaike information criterion; LM: Breusch/Godfrey LM test for residual autocorrelation; **ARCH**: ARCH test for Heteroskadasticity.

***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

	R_{big}	R_{mid}		R_{sml}	
	Model 1	**Model 1**	**Model 2**	**Model 1**	**Model 2**
α_0	0.0273 (0.09140)	0.0603 (0.1922)	0.0605 (0.1929)	-0.0658 (-0.2219)	-0.0472 (-0.1645)
R_{t-1}	-0.0938* (-1.7124)	0.0365 (0.7075)	0.0360 (0.7032)	0.2790*** (5.9043)	0.2769*** (5.7893)
R_{t-2}	-0.0168 (-0.2707)	0.0218 (0.3814)	0.0171 (0.3400)	0.0731 (1.5792)	0.0677 (1.5273)
R_{t-3}	0.0032 (0.0413)	0.0566 (0.9956)	0.0580 (1.1439)	0.1104 (1.2980)	0.1018 (1.3619)
R_{t-4}	-0.0885 (-1.5683)	-0.0213 (-0.4127)		-0.0792 (-1.4919)	-0.0674 (-1.4806)
$SENT_{t-1}$	0.0022 (0.2307)	0.0029 (0.3406)	0.0049 (1.1954)	0.0026 (0.4366)	0.0044 (1.1889)
$SENT_{t-2}$	-0.0004 (-0.0408)	0.0021 (0.1855)		-0.0013 (-0.1403)	
$SENT_{t-3}$	0.0070 (0.6198)	0.0059 (0.6162)		0.0050 (0.6214)	
$SENT_{t-4}$	-0.0073 (-0.9557)	-0.0062 (-0.9540)		-0.0013 (-0.2416)	
$SENT^{P}_{t-1}$	-0.2460 (-0.5324)	0.0985 (0.2770)	0.0744 (0.2311)	0.2070 (0.8391)	0.2219 (0.9578)
$SENT^{P}_{t-2}$	0.0027 (0.0081)	-0.4867* (-1.7376)	-0.4955* (-1.8317)	-0.4248* (-1.9193)	-0.3824** (-2.0519)
$SENT^{P}_{t-3}$	0.1968 (0.5871)	0.2524 (0.8894)	0.2288 (0.8271)	0.0858 (0.3709)	
$SENT^{P}_{t-4}$	0.0072 (0.0254)	-0.0396 (-0.1181)		-0.0389 (-01744)	
Adj. R^2	0.0005	-0.0007	0.0048	0.1183	0.131
S.E.	2.4780	2.4693	2.4597	2.0053	1.9974
AIC	4.6688	4.6618	4.6478	4.2455	4.2315
LM	1.1575	1.7244***	1.5832***	1.5101***	1.4137**
ARCH	51.8061***	48.5615***	48.3342***	25.8196***	27.3964***

Table A3: Regression of returns on weekly UK & US sentiment indexes

Table A3 reports the results of regressions of the following general form:

$$R_{size,t} = \alpha_0 + \sum_{j=1}^{4} \alpha_j R_{size,t-j} + \sum_{i=1}^{4} \beta_i SENT_{t-i} + \sum_{i=1}^{4} \gamma_i SENT_{t-i}^{p} + \sum_{i=1}^{4} \delta_i AAII_{t-i} + \sum_{i=1}^{4} \theta_i II_{t-i} + \varepsilon_t$$

The data are weekly and cover the period 1st January 1996 to 30th June 2011. The estimation method is OLS with Newey-West standard errors.

Variable definitions:

size = *big*, *mid* or *sml*; so, $\boldsymbol{R_{big}}$: return on the large-size stock portfolio; $\boldsymbol{R_{mid}}$: return on mid-size stock portfolio; $\boldsymbol{R_{small}}$: return on small-size stock portfolio; **SENT**: UK market sentiment; $\mathbf{SENT^P}$: UK institutional sentiment.

$\bar{\mathbf{R}}^2$: the Adjusted R-squared; **S.E**:Standard Error of regression; **AIC**: Akaike information criterion; LM: Breusch/Godfrey LM test for residual autocorrelation; **ARCH**: ARCH test for Heteroskadasticity. ***Statistical significance at 1% level; **Statistical significance at 5% level; *Statistical significance at 10% level.

	R_{big}		R_{mid}		R_{sml}	
	Coefficient	**t-Statistic**	**Coefficient**	**t-Statistic**	**Coefficient**	**t-Statistic**
α_0	-0.1313	-0.4344	-0.0622	-0.1943	-0.1370	-0.4611
R_{t-1}	-0.1587***	-3.1344	-0.0154	-0.3198	0.2303***	5.1540
R_{t-2}	-0.0723	-1.1046	-0.0076	-0.1287	0.0707	1.5135
R_{t-3}	-0.0486	-0.6265	0.0374	0.6835	0.1118	1.3649
R_{t-4}	-0.1129**	-2.0468	-0.0296	-0.5483	-0.0716	-1.3838
$SENT_{t-1}$	0.0003	0.0350	0.0016	0.1822	0.0012	0.2132
$SENT_{t-2}$	-0.0004	-0.0332	-0.0010	-0.0909	-0.0037	-0.4082
$SENT_{t-3}$	0.0085	0.7104	0.0077	0.8022	0.0053	0.6691
$SENT_{t-4}$	-0.0056	-0.7144	-0.0050	-0.7505	0.0005	0.0914
$SENT^P_{t-1}$	-0.2989	-0.6787	0.0083	0.0245	0.1365	0.5785
$SENT^P_{t-2}$	0.0084	0.0264	-0.5065*	-1.8643	-0.4563**	-2.0987
$SENT^P_{t-3}$	0.3191	0.9480	0.3721	1.2420	0.2077	0.8564
$SENT^P_{t-4}$	0.0699	0.2352	-0.0557	-0.1565	-0.0362	-0.1529
$AAII_{t-1}$	-0.8791	-1.4932	-0.9904	-1.4139	-0.4446	-0.7581
$AAII_{t-2}$	0.3071	0.3837	-0.2293	-0.2975	-0.7431	-1.1547
$AAII_{t-3}$	0.6143	0.8172	1.3625*	1.6674	1.3828*	1.9182
$AAII_{t-4}$	-0.2390	-0.3149	-0.4762	-0.6216	-0.1655	-0.2687
II_{t-1}	10.6719***	3.9132	12.0170***	4.6422	10.5272***	4.7110
II_{t-2}	-6.1435**	-2.3152	-9.9050***	-3.0836	-9.4091***	-3.2411
II_{t-3}	-0.5571	-0.1741	1.5109	0.4241	0.9251	0.3167
II_{t-4}	-3.9995**	-2.0150	-2.3299	-1.0471	-1.3488	-0.7246
Adj. R^2	0.0382		0.0395		0.2414	
S.E.	2.4351		2.4245		1.8657	
AIC	4.6438		4.6351		4.1160	
LM	1.1509		1.8172***		1.2199	
ARCH	42.1111***		92.0202***		16.5329***	

Table A4: Regression analysis of weekly UK sentiment measures on foreign sentiment indexes

Table A4 reports the results of estimating equations of the general form:

$$SENT_t^K = \alpha_0 + \sum_{i=1}^{4} \gamma_i AAII_{t-i} + \sum_{i=1}^{4} \delta_i II_{t-i} + \sum_{i=1}^{4} \theta_i SENTIX_{t-i} + \sum_{i=1}^{4} \beta_i SENT_{t-i}^K + \varepsilon_t$$

The data are weekly and cover the period 1st January 1996 to 30th June 2011. Exceptionally the *SENTIX* index is available only from 28th February 2001. The estimation method is OLS with Newey-West standard errors.

Variable definitions:

SENT^K = UK market sentiment (K=M), or institutional sentiment (K=P); **AAII**: American Association of Individual Investors index; **II**: American Investors Intelligence index; **SENTIX**: German equity sentiment index. t-statistics are shown in parentheses.

***Significant at 1% level; **Significant at 5% level; *Significant at 10% level.

	Including European sentiment 28/02/2001 - 30/06/2011				**Excluding European sentiment 01/01/1996 - 30/06/2011**			
	SENT		***SENT^P***		***SENT***		***SENT^P***	
	Model 1	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**
$AAII_{t-1}$	22.3316*** (5.7034)	20.1818*** (6.5024)	0.1824 (1.5758)	0.1704 (1.4934)	21.4844*** (6.7702)	21.1721*** (6.7694)	0.2147** (2.5187)	0.2156** (2.5224)
$AAII_{t-2}$	-14.8494*** (-3.5003)	–12.2305*** (-3.9048)	0.0344 (0.2910)	0.0500 (0.4351)	-10.7766*** (-3.0242)	–10.2876*** (-3.0434)	-0.0166 (-0.1934)	-0.0007 (-0.0086)
$AAII_{t-3}$	-3.9336 (-1.1605)		-0.1885* (-1.6846)	-0.1952* (-1.7807)	-4.6311 (-1.4261)	-4.5919 (-1.4742)	-0.1439 (-1.5979)	-0.1407 (-1.5667)
$AAII_{t-4}$	3.8522 (1.0880)		0.1105 (1.0428)	0.0938 (0.8911)	0.0327 (0.0102)		0.1012 (1.2387)	0.0847 (1.0562)
II_{t-1}	70.5882*** (6.3106)	68.3516*** (7.4807)	0.4538 (1.1469)	0.4801 (1.2194)	67.3856*** (7.1436)	67.2479*** (7.2519)	0.4009 (1.2773)	0.4107 (1.3070)
II_{t-2}	-29.1462 (-1.5968)	–32.3656** (-2.1129)	0.8786** (2.0117)	0.8819** (2.0126)	-34.6384** (-2.2185)	–25.2721** (-2.43941)	0.5164 (1.4087)	0.5306 (1.4394)
II_{t-3}	2.4374 (0.1650)	-7.8378 (-0.6085)	-0.7097 (-1.5580)	-0.9620*** (-2.9839)	-6.7328 (-0.5059)	–5.6663 (-0.4204)	-0.3693 (-1.9717)	-0.6236** (-2.2141)
II_{t-4}	-32.5058 (-3.1949)	–23.7306*** (-2.9904)	-0.2697 (-0.9365)		-17.9287** (-2.0906)	–23.3995*** (-2.57098)	-0.2530 (-1.0811)	
$SENTIX_{t-1}$	2.4805 (0.2349)		0.2973 (1.2294)	0.3044 (1.2790)				
$SENTIX_{t-2}$	7.9972 (0.7087)		-0.7796*** (-2.7572)	–0.7585*** (-2.7693)				
$SENTIX_{t-3}$	0.9222 (0.0848)		0.4053 (1.4078)	0.4434** (2.0010)				
$SENTIX_{t-4}$	-7.2663 (-0.8307)		0.0775 (0.3401)					
$SENT_{t-1}$	0.8193*** (17.1549)	0.8234*** (43.7837)			0.8448*** (22.8091)	0.825648*** (41.6942)		
$SENT_{t-2}$	0.0182 (0.2556)				0.0176 (0.3199)			
$SENT_{t-3}$	-0.0096 (-0.1493)				-0.0276 (-0.5357)			
$SENT_{t-4}$	-0.0442 (-1.2285)				-0.0271 (-0.7757)			
$SENT^P_{t-1}$			0.3738*** (6.4087)	0.3766*** (6.4375)			0.3249*** (6.4732)	0.3268*** (6.4626)
$SENT^P_{t-2}$			0.2328*** (4.8043)	0.2297*** (4.8081)			0.2309*** (6.5864)	0.2304*** (6.5528)
$SENT^P_{t-3}$			0.1424*** (2.8967)	0.1342*** (2.7421)			0.1260*** (3.7105)	0.1251*** (3.6767)
$SENT^P_{t-4}$			0.0865 (1.5839)	0.0895* (1.6850)			0.1568*** (3.6417)	0.1524*** (3.5121)
Adj. R^2	0.8344	0.8059	0.6881	0.6877	0.8058	0.8060	0.6165	0.6165
S.E.	10.9455	11.5380	0.3175	0.3163	11.5536	11.5412	0.3221	0.3220
AIC	7.6564	7.7391	0.5763	0.5648	7.7480	7.7409	0.5879	0.5866
LM test	1.5791***	1.2045	0.4194	0.4739	1.3880**	1.1502	1.2320	1.2474
ARCH	2.3827*	1.8583	2.4218*	2.4345*	1.8212	1.8448	10.7166***	10.9044***

Appendix 4 Methodology

A4.1. Principal Components Analysis

Principal components analysis expresses the variance-covariance structure in a set of data in such a way as to highlight their similarities and differences. This allows a specific number of time series that explain the most variation to be identified (Brown & Cliff, 2004). The orthogonal time series, extracted from the dataset, account for as much as possible of the (residual) variation. Principal components analysis has been employed to construct UK market sentiment and UK institutional sentiment index.

According to Johnson & Wichern (1992), principal components are particular linear combinations of p random variables, x_1, x_2, …, x_p:

$$y_1 = a_{11}x_1 + a_{12}x_2 + \cdots + a_{1p}x_p$$

$$y_2 = a_{21}x_1 + a_{22}x_2 + \cdots + a_{2p}x_p$$

$$\ldots$$

$$y_p = a_{p1}x_1 + a_{p2}x_2 + \cdots + a_{pp}x_p$$

The linear combinations have variance-covariance matrix, $\sum_Y = Cov(Y) = A\sum_X A'$, where $Y'(y_1, y_2, \ldots, y_p)$, $\sum_X$ is the variance-covariance matrix of X, X' $(x_1, x_2, \ldots, x_p)$, and A is the $p \times p$ matrix.

The first principal component is the linear combination with maximum overall variance, and the least principal component has the smallest variance among all linear combinations. Assuming the first principal components, y_1, is the linear combination:

$$y_1 = a_{11}x_1 + a_{12}x_2 + \cdots + a_{1p}x_p$$

It is calculated so that it accounts for the greatest possible variance in the data set, i.e. maximizes $Var(y_1) = a_1' \sum_X a_1$, subject to $a_1' a_1 = 1$ (where $a_1(a_{11}, a_{12}, \dots, a_{1p})$), since $Var(y_1)$ can be increased by multiplying any a_1 by a constant.

The second principal component is calculated such that maximizes $\mathrm{Var}(\mathrm{y}_2) = a_2' \sum_X a_2$, subject to $a_2' a_2 = 1$(where $a_2(a_{21}, a_{22}, \dots, a_{2p}))$ and uncorrelated to the first principal component.

This process continues until the last principal component is calculated, which suggests that the original variables are transformed to the principal components, since the sum of the variance of the entire principal components equal the sum of the variances of all of the variables. All principal components combined contain the same information as the original variables. However, the important information is partitioned over the components in terms of the components and orthogonal.

This procedure is now a generally accepted method of constructing measures of investor sentiment, and has been used by Brown and Cliff (2004), Baker and Wurgler (2006, 2007), Chen, Chong and Duan (2010), Baker, Wurgler, and Yuan (2012), Chen, Chong and She (2014) and Bai (2014) to construct sentiment indices by using investor sentiment proxies as the original variables.

Transforming the original variables, sentiment proxies, to the principal components:

$$Y = AX$$

where Y is the vector matrix of principal components, and X is the matrix of original variables, AVDC, CEFD, MFI, PCO PCV RSI VOLA and DVRA. The rows of matrix A are the eigenvectors, the variance-covariance matrix of the original data. The elements of an eigenvector are the weights a_{ij}, where $i, j = 1,2, \dots, p$. The first principal component of various financial market indicators is likely to provide a reliable measure of unobserved investor sentiment as it accounts for the greatest possible variance in the data set by maximizing variance of the components.

A4.2. Kalman Filter Method

The Kalman Filter addresses the general problem of estimating the state vector of a linear dynamic system. The Kalman Filter assumes that the signal and measurement process have the following structure:

$$y_t = H_t x_t + \varepsilon_t$$

$$x_{t+1} = \Phi_t x_t + \omega_t$$

where $y_t$is the measurement data which is related to X_t, ε_t and ω_t are white-noise. According to Morrison and Pike (1997), the Kalman Filter produces an estimate of x_t, $\hat{x}_t$, from the observations y_t, and the estimate is to be computed so as to minimize the mean-square error, i.e. minimizing:

$$Z(x_t) = (x_t - \hat{x}_t)^2$$

Where $x_t$is the true value and $\hat{x}_t$ minimizes the length of the error vector $x_t - \hat{x}_t$.

While each new observation y_t becomes available, it is used to update the estimate of $\hat{x}_{t-1}$, producing a new estimate, $\hat{x}_t$. The Kalman Filter is, therefore, a sequential estimation procedure for generating optimal estimates of x_t.

An alternative derivation of mean-squared error is to use maximum likelihood statistics, which defines the goal of the filter to finding the $\hat{x}_t$ which maximises the probability of y_t. Assuming that the additive random noise is Gaussian distributed with a standard deviation of σ_t, the probability of y_t is:

$$P(y_t|\hat{x}_t) = K_t exp - \left(\frac{(y_t - H_t\hat{x}_t)^2}{2\sigma_t^2}\right)$$

where K_t is a normalisation constant, and the maximum likelihood function of this is:

$$P(y|\hat{x}) = \prod_t K_t exp - \left(\frac{(y_t - H_t\hat{x}_t)^2}{2\sigma_t^2}\right)$$

Taking logarithms of the equation leads to:

$$logP(y_t|\hat{x}_t) = -2\sum_t \left(\frac{(y_t - H_t\hat{x}_t)^2}{2\sigma_t^2}\right)$$

The mean-squared error may be maximised by the variation of $\hat{x}_t,$ and provides the value of $\hat{x}_t$ which maximises the likelihood of the signal y_t.

In Section 5.6, the unobservable herding variable, H_{mt}, was estimated by applying the Kalman Filter method. By assuming the cross-sectional standard deviations of CAPM beta is the noisy observation of herding measure, the state space model is structured as:

$$log\left[Std_c\left(\beta_{imt}^b\right)\right] = \mu_m + H_{mt} + v_{mt}$$

$$H_{mt}{=}\phi_m H_{mt-1} + \eta_{mt}$$

where$Std_c(\cdot)$ represent the cross-sectional standard deviation, $\mu_m = E\left(\log\left(Std_c(\beta_{imt})\right)\right)$ $v_{mt}{\sim}iid(0, \sigma_v^2)$ and $\eta_{mt}{\sim}iid\left(0, \sigma_{m\eta}^2\right)$. The estimated H_{mt} is to be computed so as to minimize the mean-square error or maximises the likelihood of the $log\left[Std_c\left(\beta_{imt}^b\right)\right]$.

In order to compute time-varying betas in 5.6.2, CAPM model is casted in ‘state space’ (Black, Fraser and Power, 1992):

$$\left(r_{pt} - r_{ft}\right) = \alpha + \beta_t\left(r_{mt} - r_{ft}\right) + \xi_t$$

$$\beta_t = \beta_{t-1} + \nu_t$$

Where r_{pt} is the return of portfolio, r_{ft} is the risk-free return and r_{mt} is the market return at time t. $\left(r_{pt} - r_{ft}\right)$ is an $n \times k$ known matrix; ξ_t is an $n \times 1$ vector and $\xi_t \sim N(0, \Omega_t)$; ν_t is a $k \times 1$ vector and $\nu_t \sim N(0, Q_t)$.

The parameter β is allowed to vary over time and the information on the dependent variable is available. The Kalman filter is applied to compute optimal estimates of β_t from an initial estimate of β_{t-1} and its covariance matrix, P_{t-1} by minimum mean square linear estimation. The prediction equation for the state vector β_t and its covariance matrix, P_t is

$$\beta_{t|t-1} = \beta_{t-1}$$

$$P_{t|t-1} = P_{t-1} + Q_t$$

The updating of the state equation by incorporating the new information from the prediction error of the minimum mean square linear estimation:

$$\beta_t = \beta_{t|t-1} + \frac{P_{t|t-1} z_t\left[\left(r_{pt} - r_{ft}\right) - z_t' \beta_{t|t-1}\right]}{z_t' P_{t|t-1} z_t} + h_t$$

Where h_t is the covariance matrix of ξ_t and the $P_{t|t-1} z_t / z_t' P_{t|t-1} z_t$ is the $(n \times 1)$ vector of the Kalman gain. $z_t'\left(\beta_t - \beta_{t|t-1}\right) + \xi_t$ is the error made in predicting the minimum mean square linear estimation at $t-1$. The one step ahead prediction errors and their covariance matrix can be used in the likelihood function, and equations predict and updated by using all the available information incorporated at the end of the period.

Bibliography

Abreu, D. and Brunnermeier, M.K. (2003) Bubbles and Crashes, *Econometrica*, Vol. 71(1), pp:173-204

Agudo, L.F., Sarto, J.L. and Vicente, L. (2008) Herding behavior in Spanish equity funds *Applied Economics Letters* Vol.15, pp:573-576

Ammer, J. M., (1990) Expenses, yields, and excess returns: New evidence on closed-end fund discounts from the UK, LSE Financial Markets Group Discussion Paper No, 108

Andrews, D.W.K. and Monahan, J.C. (1990) An Improved Heteroskedasticity and Autocorrelation Consistent Covariance Matrix Estimator, *Cowles Foundation Discussion Paper No. 942, Yale University*

Baddeley, M. (2010) Herding, social influence and economic decision-making: socio-psychological and neuroscientific analyses *Philosophical Transactions of The royal Society* Vol. 365, pp. 281-290

Bai, Y. (2014) Cross-border sentiment: an empirical analysis on EU stock markets, *Applied Financial Economics*, Vol. 24(4), pp: 259-290.

Baker, M., Stein, J.C (2004) Market liquidity as a sentiment indicator *Journal of Financial Market*, Vol. 7(3), pp: 271-299

Baker, M., Wurgler, J. (2006) Investor Sentiment and the Cross-Section of Stock Returns *The Journal of Finance*, Vol. LXI, No. 4, pp 1645-80

Baker, M., and Wurgler, J. (2007) Investor Sentiment in the Stock Market *Journal of Economic Perspectives* 21(2): 129–151

Baker, M., Wurgler, J. and Yuan, Y. (2012) Global, Local, and Contagious Investor Sentiment *Journal of Financial Economics*, Vol. 104, pp 272-287

Bandopadhyaya, A., Jones, A.L. (2006) Measuring Investor Sentiment in Equity Markets *Journal of Asset Management,* Vol. 7, pp: 208-215

Bandopadhyaya, A., Jones, A.L. (2008) Measures of Investor Sentiment: A comparative analysis put-call ratio vs. Volatility index *Journal of Business & Economics Research* Vol. 6, No. 8, pp: 27-33

Banerjee, A.V. (1993) The economics of Rumours *Review of Economic Studies* Vol. 68, pp: 308 -327

Barber, B.M., Odean, T. & Zhu, N. (2009) Systematic noise *Journal of Financial Markets* Vol. 12, pp: 547-569

Barber, B. M., Odean, T. and Zhu, N. (2009) Do Retail Trades Move Markets? *Review of Financial Studies*, Vol. 22(1), pp:151-186

Barberis, N, Huang, M., & Santos, T. (2001) Prospect theory and asset price *Quarterly Journal of Economics*, 116(1):1-53

Barberis, Nicholas, Andrei Shleifer, and Robert Vishny, (1998) A Model of Investor Sentiment *Journal of Financial Economics*, 49(3):307-43

Barberis, N. And Thaler, R. (2003) A survey of Behavioral Finance *Handbook of the Economics of Finance* Vol. 1 Part 2, pp1053-1128

Bandopadhyaya, A., Jones, A.L. (2006) Measuring Investor Sentiment in Equity Markets *Journal of Asset Management*, Vol7(3), pp: 208-215

Banerjee, A.V. (1992) A Simple model of herd behaviour *The Quarterly Journal of Economics*, Vol. 107, No. 3, pp. 797-817

Beaumont, R., van Daele, M., Frijns, B., Lehnert, T. (2005) On Individual and Institutional Noise Trading *Working Paper, Maastricht University*

Beckmann, J., Belke A. and Kühl,M., (2011) Global Integration of Central and Eastern European Financial Markets—The Role of Economic Sentiments. *Review of International Economics*, Vol. 19(1), pp: 137-157.

Bennett, J. A., Sias, R. W. and Starks, L.T. (2003) Greener pastures and the impact of dynamic institutional preferences *The Review of Financial Studies*, Vol. 16, pp: 1203-1238

Bernard, V.L., Thomas, J.K. (1990) Evidence that stock prices do not fully reflect the implications of current earnings for future earnings *Journal of Accounting and Economics* Vol. 13, pp: 305-340

Bertin, W.J., Prather, L. (2009) Management structure and the performance of funds of mutual funds *Journal of Business Research* Vol. 62(12), pp1364-9

Bikhchandani, S. Hirshleifer, D. and Welch, I. (1992) A theory of fashion fads, custom and cultural changes as informational cascades *Journal of Political Economy*, 100(5): pp 992-1026

Bikhchandani, S., Sharma, S. (2001) Herd Behaviour in Financial Markets *IMF Staff Papers*, Vol.47, No. 3

Black, A., Fraser, P., and Power, D. (1992) UK unit trust performance 1980-1989: A passive time-varying approach, *Journal of Banking and Finance* Vol. 16, pp:1015-1033
Black, F. (1986) Noise *Journal of Finance* Vol. 41, pp:529-43

Boco, H., Germain, L., Rousseau, F. (2010) When Overconfident Traders Meet Feedback Traders *Working paper series, International Conference of the French Finance Association*, May 11-13, 2011

Brennan, M.J., (1990) Latent assets, *Journal of Finance* Vol.45, pp: 709-730

Brown, Gregory W. (1999) Volatility, Sentiment, and Noise Traders *Financial Analysts Journal* Vol. 55, No.2: 82-90

Brown, G.W., and Cliff, M.T. (1999) Sentiment and the stock market *Working paper, University of North Carolina*, Chapel Hill

Brown, G.W., and Cliff, M.T. (2004) Investor sentiment and the near-term stock market *Journal of Empirical Finance*, Vol. 11(1), 1-27

Brown, G.W., and Cliff, M.T. (2005) Investor sentiment and asset valuation *Journal of Business*, Vol. 78(2), 405-440

Brown, J., Ivković, Z., Smith, P. and Weisbenner, S., (2008) Neighbours matter: causal community effects and stock market participation. *Journal of Finance*, Vol. 63, pp: 1509–1531

Burghardt, M. (2010) Retail Investor Sentiment and Behavior – an Empirical Analysis *Dissertation, Karlsruhe Institute of Technology*

Caballe, J., and Sakovics, J. (2003) Speculation against an overconfident market *Journal of Financial Market* Vol.6, pp: 199-225

Campbell, J.Y., Kyle, A.S. (1993) Smart Money, Noise Trading and Stock Price Behaviour *The Review of Economic Studies*, Vol. 60(1), pp: 1-34

Campbell, J., Lettau, M., Malkiel, B. and Xu, Y. (2001) Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk,*Journal of Finance*, Vol. 49(1), pp.1-43.

Caparrelli, F., D'Arcangelis, A.M. & Cassuto, A. (2004). Herding in the Italian Stock Market: A Case of Behavioral Finance *The Journal of Behavioral Finance* , Vol. 5(4), pp: 222-230.

Caporale, G.M., Economou, F. and Philippas, N. (2008) Herd Behaviour in Extreme Market Conditions: The case of the Athens Stock Exchange *Economics Bulletin*, Vol.7, No.17, pp:1-13

Chang, E. C., Cheng, J. W. and Khorana, A. (2000) An examination of herd behavior in equity markets: an international perspective *Journal of Banking and Finance,* Vol. 24, pp:1651–1679.

Caparrelli, F., D'Arcangelis, A.M. and Cassuto, A. (2004) Herding in the Italian Stock Market: A case of Behavioral Finance *The Journal of Behavioral Finance*, Vol. 5(4), pp: 222-230

Chen, H., Chong, T.T-L., Duan, X. (2010) A principal-component approach to measuring investor sentiment *Quantitative Finance*, 10:4, 339-347

Chen, H., Chong, T.T-L., and She, Y. (2014) A Principal Component Approach to measuring Investor Sentiment in China, *MIPRA Paper No. 54151*, *http://mpra.ub.uni-muenchen.de/54150/*

Choe, H., Kho, B and Stulz, R., (1999) Do foreign investors destabilize stock markets? The Korean experience in 1997 *Journal of Financial Economics* Vol. 54, pp: 227-64

Christie, W.G. and Huang, R.D., (1995) Following the Pied Piper: Do Individual Returns Herd around the Market *Financial Analysts Journal*, July-August, pp: 31-37

Coase, R. H. (1988) The Firm, the Market, and the Law*University of Chicago Press*

Cornell, B. (1985) Taxes and the pricing of stock index futures: Empirical results *Journal of Futures Markets*, Vol 5(1), pp: 89-101

Cross, F. (1973) The Behavior of Stock Prices on Fridays and Mondays, Financial Analysts Journal, Vol 29(6), pp. 67-69

Cutler, D., Poterba, J., and Summers, L., (1991) Speculative dynamics *Review of Economic Studies*, Vol. 58, pp: 529-46

Daniel, K., Hirshleifer, D and Subrahmanyam, A. (1998) Investor psychology and Security market under-and overreactions *The Journal of Finance* Vol.53(6), pp: 1839-1885

Daniel, K., Hirshleifer, D and Subrahmanyam, A. (2001) Overconfidence, Arbitrage and Equilibrium Asset Price *The Journal of Finance* Vol.56(3), pp: 921-965

DeBondt, W.F.M., Thaler, R.H., (1985) Does The Stock Market Overreact? *Journal of Finance* Vol. 40, pp. 793-808

Degeorge, F., Patel, J. and Zeckhauser, R. (1999) Earnings management to exceed thresholds.*Journal of Business* Vol.72, PP: 1-33.

DeLong, J.B., Shleifer, A., Summers, S.H., and Waldmann, R.J. (1990) Positive feedback investment strategies and destabilizing rational speculation *The Journal of Finance* Vol. 45(2), p379-395

DeLong, B., Shleifer, A., Summers, L. And Waldmann, R. (1990) Noise trader risk in financial markets. *Journal of Political Economy*, 98: 703-738

De Long, B., Shleifer, A., Summers, L. And Waldmann, R. (1991) The survival of noise traders in financial markets *Journal of Business*, Vol. 64(1) pp: 1-19

Demirer, R., Kutan, A.M., (2006) Does herding behaviour exist in Chinese stock markets? *Journal of Financial Markets, Institutions and Money* Vol. 16(2), pp: 123-142

Demirer, R., Kutan, A.M., and Chen, C.D. (2010) Do investor herd in emerging stock markets?: Evidence from the Taiwanese market *Journal of Economic Behaviour & Organization* Vol. 76, pp:283-295

Dreman, D. (1979) *Contrarian Investment Strategy: The Psychology of Stock Market Success* Random House, New York

Dyl, E.A. and Maberly, E.D. (1988), A possible explanation of the weekend effect, *Financial Analyst Journal*, Vol: 43(3), pp 83-4

Einhorn, H. and Gigarth, R. (1978) Confidence in judgment Persistence of the illusion of validity *Psychological Review* 85, pp: 581-97

Fama, E.F. (1965) The behaviour of stock-market prices *The Journal of Business*, Vol. 38(1), pp: 34-105

Fama, E.F. (1970) Efficient capital markets: A review of theory and empirical work *Journal of Finance*, Vol. 25, pp: 283-417

Fama, E.F., Fisher, L., Jensen, M.C., Roll, R. (1969) The Adjustment of Stock Prices to New Information *International Economic Review*, Vol. 10(1), pp:1-21

Fama, E.F., & French K.R. (2006), The Value Premium and the CAPM, The Journal of Finance, Vol.61(5), pp: 2163-2185

Fong. W.M., (2013) Risk Preferences, Investor Sentiment and Lottery Stocks: A Stochastic Dominance Approach. *The Journal of Behavioral Finance*, Vol. 14, pp. 42-52

French, K.R. (1980) Stock returns and the weekend effect, *Journal of Financial Economics*, Vol. 8(1), pp: 55-69

Friedman, B.M. (1953) The case for flexible exchange rates *In M. Friedman,Essays in Positive Economics*, Chicago University of Chicago Press

Friedman, B.M. (1984) A Comment: Stock prices and social dynamics *Brookings Papers on Economic Activity* Vol. 2, pp. 504-508

Forbes, W. (2009) *Behavioural Finance John* Wiley & Sons Ltd,

Froot, K.A., Scharfstein, D.S. and Stein, J.C. (1992) Herd on the Street: Informational Inefficiencies in a Market with Short-Term Speculation *Journal of Finance*, 47, pp: 1451-84

Gleason, K.C., Lee, C.I. and Mathur, I. (2003) Herding Behavior in European Futures Markets *Finance Letters*, Vol. 1, pp: 5-8

Gleason, K.C., Mathur, I., and Peterson, M.A. (2004) Analysis of intraday herding behaviour among the sector ETFs *Journal of Empirical finance* Vol. 1, pp: 691-694

Graham, J.R. (1999) Herding among Investment Newsletters: Theory and Evidence, *The Journal of Finance*, Vol. 54 (1), pp: 237-268

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

Han, B. (2008) Investor Sentiment and Option Price *Review of Financial Studies* Vol. 21(1), pp: 387-414

Hansen, L.P. and Hodrick, R.J. (1980) Forward Exchange Rates as Optimal Predictors of Future Spot Rates: An Econometric Analysis, *Journal of Political Economy*, Vol. 88(5), pp: 829-853

Harri, A., and Brorsen, B.W. (2009) The Overlapping Data Problem. *Quantitative and Qualitative Analysis in Social Sciences* Vol. 3(3), pp:78-115.

Hayek, F.A (1952) *The Sensory Order: An Inquiry Into The Foundations of Theoretical Psychology* The University of Chicago Press

Hirshleifer, D., Subrahmanyam, A., and Titman, S. (1994) Security analysis and trading patterns when some investors receive information before others *Journal of Finance* Vol. 49, pp: 1665-98

Hirshleifer, D., Teoh, S.H. (2003) Herding Behaviour and Cascading in Capital Markets: a Review and Synthesis *European Financial Management* Vol. 9(1), pp: 25-66

Hong, G., and Yi, K., (2006) On the herding behavior of fund managers in the Korean stock market *Asia Pacific Journal of Financial Studies* Vol. 35(4), pp: 1-38

Hong, H, and Stein, J.C (1999) A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets The Journal of Finance Vol. 54(6), pp: 2143-2184

Hwang, S. and Salmon, M. (2004) Market stress and herding *Journal of Empirical finance* 11, pp: 585-616

Hwang, S. and Salmon, M. (2007) Sentiment and Beta Herding. *Working paper*

Jackson, A. (2003) The Aggregate Behaviour of Individual Investors *Working paper, London Business School.*

Jegadeesh, N., Titman, S. (1993) Return to buying winner and selling losers: implications for stock market efficiency *Journal of Finance* Vol. 48(1), pp: 65-91

Jensen, M.C. (1967) The Performance of Mutual Funds in the Period 1945-1964 *Journal of Finance* Vol. 23(2), pp: 389-416

Johnson, R.A., and Wichern, D.W. (1992) Applied Multivariate Statistical Analysis (3rd ed.) Englewood Cliffs, NJ: Prentice-Hall

Kahneman, D. & Riepe, M.W. (1998).Aspects of investor psychology.*Journal of Portfolio Management*, Vol. 24(4), pp: 52-65.

Kahneman, D. & Tversky, A. (1973).On the psychology of prediction. *Psychological Review* 80 pp: 237–251

Kahneman, D. & Tversky, A. (1974) Judgment under Uncertainty: Heuristics and Biases *Science, New Series,* Vol. 185, pp: 1124-1131

Kahneman, D. & Tversky, A. (1979) Prospect Theory: An Analysis of Decission Under Risk *Econometrica* Vol. 47(2) pp: 263-91

Kahneman, D., Slovic, P., and Tversky, A (eds) (1982) *Judgment under uncertainty heuristics and biases* Cambridge, Cambridge University Press

Kapanski, G. & Levy, H. (2011) Analysts and Sentiment: A Causality Study, Working paper, *SSRN: http://ssrn.com/abstract=1866265*

Keim, D.B. (1983) Size-related anomalies and stock return seasonality: Further empirical evidence *Journal of Financial Economics*Vol. 12(1), pp: 13-32

Khan, H., Hassairi, S.A., & Viviani, J.L., (2011) Herd Behavior and Market Stress: The Case of Four European Countries, *International Business Research*, vol. 4(3) pp. 53- 67

Kling, G. and Gao, L. (2008) Chinese institutional investors' sentiment *Journal of International Financial Market and Money*, 18: 374-387

Kraus, A. and Stoll, H. (1972). Price impacts of block trading on the new york stock exchange. *Journal of Finance* Vol. 27, pp: 569–588.

Kumar, A. and Lee, C.M.C. (2006) Retail Investor Sentiment and Return Comovements, *The Journal of finance*, Vol. 61(5), pp: 2451-2486

Kyle, A.S, and Wang, F.A. (1997) Speculation duopoly with agreement to disagree: Can overconfidence survive the market test? *Journal of Finance* Vol. 52, pp: 2073-2090

Lakonishok, J., Shleifer, A., & Vishny, R.W. 1992, The impact of institutional trading on stock prices *Journal of Financial Economics* Vol. 32, pp: 23-43

Lao, P. and Singh, H. (2011) Herding Behaviour in the Chinese and India Stock Markets, *Journal of Asian Economics*, Vol. 22(6), pp: 495-506

LeRoy, S. F., Porter, R. D. (1981) The present value relation: Tests based on implied variance bounds. *Econometrica*, Vol. 49, PP: 555—574

Lee, C.M.C., Shleifer, A., Thaler, R.H., 1991, Investor Sentiment and the Closed-End Fund Puzzle *Journal of Finance*, 46, 75-109

Lee, W.Y., Jiang, C.X. and Indro, D.C. (2002) Stock market volatility, excess returns, and the role of investor sentiment *Journal of Banking & Finance*, Vol. 26, pp: 2277-99

Lee, W.Y., Jiang, C.X., Indro, D.C. (2002) Stock market volatility, excess returns, and the role of investor sentiment *Journal of Banking & Finance* 26 (2002) 2277–2299

Lemmon M.L. and Ni, S.X. (2008), “The Effects of Investor Sentiment on Speculative Trading and Prices of Stock and Index Options”, *HK University of Science & Technology, SSRN: http://ssrn.com/abstract=1306237*.

Lewellen, J. (2009) Institutional investors and the limits of arbitrage *working paper, Dartmouth College and NBER*, first draft 2007

Liao, T.L., Huang, C.J. and Wu, C.Y. (2011) Do Fund Managers Herd to Counter Investor Sentiment? *Journal of Business Research*, Vol. 64(2), pp: 207-212

Lichtenstein, S., Fischoff, B., Phillips, L.D. (1982). Calibration of probabilities: The state of the art to 1980. *In Daniel Kahneman, Paul Slovic, Amos Tversky. Judgment under uncertainty: Heuristics and biases.*Cambridge University Press. pp. 306–334

Lin, Y. and Swanson, P.E. (2003) The Behavior and Performance of Foreign Investors in Emerging Equity Markets: Evidence from Taiwan, *International Review of Finance*, Vol. 4(3-4), pp: 189-210

Lowenstein, R. (2000) When Genius Failed: The Rise and Fall of Long-Term Capital Management, Random House Trade

Lux, T. and Marchesi, M. (1999) Scaling and Criticality in a Stochastic Multi-agent Model of a Financial Market, *Nature*, Vol. 397, pp: 498-500

Mandelbro, B.B. (1963) The Variation of Certain Speculative Prices *Journal of Business* Vol. 36, pp: 394-419

Maug, C.F., and Naik, N. (1996) Herding and Delegated Portfolio Management *working paper, London Business School*

Morrison, G.W. and Pike, D.H. (1997) Kalman Filtering Applied to Statistical Forecasting *Management Science* Vol.23(7), pp.768-774

Newey, W.K. and West, K.D. (1987) Hypothesis Testing with Efficient Method of Moments Estimation, International Economic Review, Vol. 2/(3), pp: 777-787

Nofsinger, J.R., and Sias, R.W. (1999) Herding and Feedback Trading by Institutional and Individual Investors *The Journal of Finance* Vol. 54, No. 6, pp. 2263-2295

Odean, T. (1998) Volume, Volatility, Price, and Profit when all traders are above average *Journal of Finance*, Vol.53(6), pp: 1887-934

Qiu,L.X., Welch, I. (2006) Investor sentiment Measures *Working Paper, Brown University*

Claudio, R., and Schmukler, S.L., (2012) On the international transmission of shocks: Micro-evidence from mutual fund portfolios *Journal of International Economics, Elsevier*, vol. 88(2), pp: 357-374.

Scharfstein, D.S. and Stein, J. (1990) Herd behaviour and investment *The American Economic Association* Vol. 80(3), p465-479

Sabherwal, S., Sarkar, S.K. and Zhang, Y., (2011) Do Internet Stock Message Boards Influence Trading? Evidence from Heavily Discussed Stocks with No Fundamental News.*Journal of Business Finance and Accounting*, Vol. 38(9-10), pp: 1209–1237

Schmeling, M. (2009) Investor sentiment and stock returns: Some international evidence *Journal of Empirical Finance*, Vol. 16, p394-408

Sharpe, W.J. and Alexander, G.J., (1990) Investments 4th ed. edn. Prentice-Hall International, Inc.

Sherif, M. and Murphy, G., (1936) The psychology of social norms, *Harper & Brothers*

Shiller, R.J. (1981) Do Stock Prices Move Too Much to be Justified by Subsequent Changes in Dividends? *American Economic Review* Vol. 71(3), pp: 421–436

Shiller, R. J. (1984) Stock Prices and Social Dynamics *Brookings Papers on Economic Activity*, pp: 457-98

Shiller, R.J. (1995) Conversation, Information, and Herd Behavior, The American Economic Review, Vol. 85(2) pp:181-185

Shiller, R.J. (2003) From Efficient markets theory to behavioral finance *Journal of Economic Perspectives*, Vol. 17(1), pp: 83-104

Shiller, R.J. and Pound, J. (1989) Survey evidence on diffusion of interest and information amount investors *Journal of Economic Behavior and Organization*, Vol. 81, pp: 227-231

Shleifer, A. (2000) *Inefficient Market* Oxford University Press

Shleifer, A., and Vishny, R. (1997) The limits of arbitrage *Journal of Finance* Vol. 52, pp: 35-55

Sias, R.W. (2004) Institutional Herding, *The Review of Financial Studies*, Vol. 17(1), pp: 165-206

Siegel, J.J. (1998) Stocks for the Long Run.*New York: McGraw Hill*

Simon, H.A. (1991) Bounded Rationality and Organizational Learning. *Organization Science* Vo. 2 (1), pp: 125–134

Stein, J.C (2005) Why Are Most Funds Open-End? Competition and the Limits of Arbitrage, *Quarterly Journal of Economics*, Vol.120, pp: 247-272.

Subrahmanyam, A. (2005) Distinguishing Between Rationales for Short-Horizon Predictability of Stock Returns *The Financial Review* Vol. 40, pp: 11-35

Tan, L., Chiang, T.C., Mason, J.R., Nelling, E. (2008) Herding behaviour in Chinese stock markets: An examination of A and B shares *Pacific-Basin Finance Journal* 16 (2008), 61-77

Tarde, G.D. and Parsons, E.W.C. (1903) The laws of imitation, *H. Holt and Company*

Trueman, B. (1994) Analysts Forecasts and Herd Behavior.*Review of financial studies*, Vol. 7, pp: 97-124

Tversky, A. and Kahneman, D. (1986) Rational Choice and the Framing of Decisions *The Journal of Business* Vol. 59(4), pp S251-S278

Verma R, Soydemir G (2006) The impact of U.S. individual and institutional investor sentiment on foreign stock markets. *Journal of Behavioral Finance*Vol. 7(3), pp: 128–144

Verma, R. and Verma, P. (2007) Noise trading and stock market volatility *Journal of Multinational Financial Management* Vol. 17, pp.: 231-243

Wang, F.A. (1998) Strategic trading, asymmetric information and heterogeneous prior beliefs *Journal of Financial Markets* Vol. 1(3-4), pp: 321-352

Wang, M. & Sun, J. (2004) Stock Market Returns, Volatility and the Role of Investor Sentiment in China *Economic Research Journal* Vol.10 pp 75-83 (published in Chinese)

Wang, Y.H., Keswani. A., and Taylor, S.J. (2006) The relationships between sentiment, returns and volatility *International Journal of Forecasting* 22, pp: 109-123

Welch, I. (2000) Herding among security analysts *Journal of Financial Economics* Vol. 58, pp. 369-396

Wermers, R. (1999) Mutual found herding and the impact on stock price *Journal of Finance* Vol. 54(2), pp: 581-622

Wurgler, J., Bradley, B., Baker, M. (2010) A behavioural finance explanation for the success of low volatility portfolios *New York University Stern School of Business Working paper* January 2010, http://hdl.handle.net/245/29537

Wylie, S. (2005) Fund Manager Herding: A Test of the Accuracy of Empirical Results Using U.K. Data *Journal of Business* Vol.78, no.1, pp: 381-403

Xu, Y. and Green, C.J., (2013) A Conditional Asset Pricing Model with Investor Sentiment: Evidence from Chinese Stock Markets. *The Manchester School*, Vol. 81(1), pp. 1-32.

Yu, J. and Yuan, Y., (2011) Investor sentiment and the mean–variance relation.*Journal of Financial Economics*, Vol. 100, pp. 367–381.

Zouaoui, M., Nouyrigat, G., and Beer, F. (2011) How Does Investor Sentiment Affect Stock Market Crises? Evidence from Panel Data *The Financial Review* Vol. 46, pp: 723-747

Zwiebel, J. (1995) Corporate Conservatism and Relative Compensation.*Journal of Political Economy*, Vol. 103(1), pp: 1-25

Zweig, M.E., (1973) An Investor expectation stock price predictive model using closed-end fund premiums, *The Journal of Finance* Vol. 28, pp: 67-87