Behavioural Finance, Options Markets and Financial Crises: Application to the UK Market 1998-2010

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Abstract

This thesis examines the relationship between behavioural finance and options markets. Particular focus is on the analysis of option prices, implied volatility and trading activity which in turn provides insights into predictability, momentum and overreaction.

The thesis is contextualised by a general to specific evaluation of the literature that forms the basis of the behavioural finance paradigm. The review is extended to analyse the extent to which support for the behavioural finance approach has been produced by research on options. Behavioural finance retains an element of controversy as it runs counter to a key pillar of neoclassical finance, the efficient markets hypothesis. Hence the onus is on researchers in this field to produce evidence that refutes the notion of market efficiency and to build models with testable implications that are better able to capture the mechanics of financial markets.

This thesis is motivated by a desire to investigate, in detail, key aspects of human behaviour and to test whether they are particularly apparent in options markets. It is important to study the information which can be extracted from options data and to analyse whether this has any predictive power for spot prices. By extension, it is of further interest to examine whether movements in spot prices exert influence on option prices. In particular, aspects of options that capture human behaviour such as pricing of puts relative to calls, implied volatility, trading volume and open interest. The topical relevance of the work is highlighted by thorough application to the UK market during two recent periods of intense financial turbulence; the bursting of the dotcom bubble in 2001 and the liquidity/banking crisis of 2007/8.

The empirical work examines the pricing of exchange-traded options relative to theoretical values, the forecasting performance of implied volatility indexes, the ability of trading volume and open interest to capture behavioural aspects of trading behaviour, and momentum and overreaction effects. Hence the work provides a unique and thorough investigation into behavioural finance and options markets in the UK. Results indicate an important role for investor sentiment although they do not necessarily indicate exploitable inefficiencies.

Declaration

No part of this thesis has been submitted elsewhere for any other degree or qualification in this or any other university. It is all my own work unless referenced to the contrary in the text.

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I would like to thank my colleagues for their advice, support and patience during the preparation of this thesis. I am indebted to Toby Watson for invaluable assistance through numerous data collection and organisation crises. Also sincere thanks to David Barr, Arthur Walker and Ian Lincoln for useful and insightful guidance and comments. All of your help is much appreciated.

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INTRODUCTION

The overall objective of this thesis is to examine options markets for evidence of behavioural factors. Rather than evaluate behavioural factors in options more generally, this study focuses on a fairly recent time period containing two sub-periods of high market volatility; the burst of the dot com bubble in 2000 and the financial crisis of 2007/8. A number of approaches are adopted to pursue the central objective. The behaviour of option prices and implied volatility are examined prior to, and during the burst of the dot com bubble in order to establish whether they contain any predictive ability for future market moves. A UK implied volatility index is constructed which covers the period before, during and after the 2007/8 crisis. The index's forecasting ability for future volatility and predictive ability for future market returns is then analysed. A sentiment measure is constructed, using trading volume and open interest of FTSE100 index options and options written on the stocks of financial stocks, and used to test for predictive power. Furthermore, the sentiment measure is analysed following sharp, consecutive short-term market moves of a consistent sign. The objective is to test whether trading behaviour is induced by perceived trends. Standard option pricing models do not incorporate price pressure as a parameter. This study hypothesises that demand is an important parameter in the pricing of options. A non-parametric approach is adopted to test for momentum effects before, during and after the 2007/8 financial crisis. The non-parametric approach involves evaluating put-call parity violations following 60-day positive and negative market returns. Momentum tests are also performed by employing a parametric approach which involves analysis of the behaviour of implied volatility spreads following positive and negative market returns. If momentum effects are identified in options markets then this implies that demand provides an additional parameter in option pricing. Finally the relationship between implied volatility and realised volatility, conditional on short-run significant price changes in the underlying index, is examined. The hypothesis to be tested is that options market investors in the UK overreact to short term moves in the underlying index.

The thesis begins by contextualising the empirical chapters. This is done by reviewing important historical and more recent literature in the field of behavioural finance generally. This is followed by a second review chapter which focuses on research into behavioural finance and options markets. Behavioural finance presents an important and growing challenge to the neoclassical finance paradigm and involves the application of cognitive psychology to analyse human behaviour in financial markets. Why is behavioural finance important? The desire to build alternative models has arisen because neoclassical finance theory does not appear to explain adequately a number of aspects of human behaviour within financial markets. For example, why do individuals trade frequently? What rules or guidelines do investors use to construct portfolios and how well do these portfolios perform? Why do we observe variation in returns across investments in financial assets for reasons other than risk' or more precisely how investors perceive risk?[1] Questions of this nature do not appear to be satisfactorily addressed by models of traditional finance and pose significant problems for the efficient markets hypothesis.

A substantial body of literature within finance, and particularly within asset-pricing, is based on the assumption of an efficient capital market (see *inter alia* Kendall, 1953, Fama, 1970) and rational investor behaviour. In an efficient capital market the prices of securities will reflect all relevant available information. This implies that any new

[1] Key questions adapted from Subrahmanyam (2007).

information revealed about a firm will be recognised by market participants who will then update their views accordingly. Thus the information will be rapidly impounded into that firm's security prices and investors will not be able to make consistent abnormal profits by trading on the basis of information after it has been revealed. It follows that investors should only be able to consistently make fair returns on average, based upon the risks associated with the securities they have invested in. In such circumstances fairly and correctly priced securities provide reliable information on which to base financial decisions.

The relatively new research area of behavioural finance runs counter to the efficient markets hypothesis and the notion of the fully rational investor. A key aspect of behavioural finance theories is that investors make systematic errors, which can result in a sustained shift of security prices away from their fundamental values. Increasingly, behavioural finance is addressing, and in many cases providing plausible explanations of, many apparent inefficiencies, anomalies and irrational investor behaviour in financial markets. Some key research topics and examples of interesting contributions to the literature are as follows:

- Excess Volatility (Shiller, 1981, LeRoy and Porter, 1981)
- Overreaction (DeBondt and Thaler, 1985, Daniel, Hirshleifer and Subramanyam, 1998)
- Disposition effect (Shefrin and Statman, 1985)
- Predictability (Fama and French, 1988)
- Conservatism and underreaction (Barberis, Shleifer and Vishny, 1998)
- Closed end fund puzzle (Lee, Shleifer and Thaler, 1991, Shleifer, 2000)
- Excessive trading (Odean, 1999)

- Abnormal price movements relating to events such as mergers, share repurchases and IPOs (Ikenberry, Lakonishok and Vermaelen, 1995)
- Collective behaviour (Sentana and Wadhwani, 1992)
- Speculative bubbles in equity markets in the late 1990s and subsequent downturn in 2000/2001. Irrational Exuberance (Shiller, 2000).

The behavioural arguments offered in much of the literature have gained momentum over recent years and have become increasingly persuasive. In particular, these arguments provide an attractive alternative approach when considered in the context of the difficulties that traditional models face in explaining many previously unexplained market phenomena.

It may at first seem counter-intuitive to analyse behavioural finance in derivative markets and in particular options markets. In conventional finance the price of a derivative is tied strongly to that of the underlying asset by arbitrage conditions. For example, the Black-Scholes (1973) option pricing model is derived by constructing an instantaneously riskless no-arbitrage portfolio of stocks and options. If the cash flows of the derivative can be replicated by implementing a dynamic strategy using stocks and riskless bonds then the derivative is regarded as a redundant asset. However, the fact that options not only exist but are also extensively traded indicates that market participants do not perceive them as redundant assets. The options market provides investors with the opportunity to enhance their utility by expanding the range of risk management and leverage opportunities available. An option gives the holder the opportunity to transfer risk to another individual who, in return for a fee, is willing to accept that risk. Hence investors are able to avoid regret by using the options market. Options also facilitate leveraged speculation in stocks with limited downside risk. Options, particularly index options have low transactions costs compared to the underlying assets. For example, contrast the cost of shorting all of the constituent stocks in the FTSE100 in their value-weighted proportions with the cost of buying a FTSE100 put option. Furthermore, it is not necessarily correct to assume that the options market is populated by the same individuals who populate the equity market. Nor should it be assumed that each population share the same degree of sophistication.

Relatively recent literature has been published which identifies behavioural issues such as overreaction, momentum, predictability, loss aversion and narrow framing in options markets or, more precisely, individuals trading in these markets. It is therefore a worthwhile exercise to compile a significant quantity of theory and evidence on this apparently anomalous activity into a single study and to perform some further empirical analysis to potentially produce evidence of behavioural biases in options markets. In particular it is important to investigate whether we can identify aspects of investor behaviour before, during and after periods of significant market turbulence from options market data. In this study the ‘dotcom bubble’ and ‘liquidity crisis’ periods of the early 21st century will be examined by focusing on the key indicators of option market activity identified above. Options can be used to reveal the risk-neutral distribution and investor preferences. Although extensive analysis has been performed on US data there is much less published work that examines the UK market.

The motivation for this thesis is to provide an in depth critical evaluation of the behavioural finance paradigm and to facilitate a better understanding of the role of human behaviour in the operation of options markets. A thorough understanding of the concepts and issues is important for practitioners and for the creation of knowledge through academic research. Chapter 1 carries out a thorough critical review of the behavioural finance literature with focus on key concepts and issues in equity markets. Chapter 2 builds on Chapter 1 by identifying and discussing the important behavioural aspects of options markets in a critical review of this more specialised literature. This in turn serves to motivate the empirical analysis carried out in the following chapters.

Unfortunately, the existing literature on behavioural finance and options markets is limited in its scope with the vast majority of published literature focused on the United States and concentrated on equity markets. This study addresses the gap in the literature by pulling together and reviewing the key behavioural contributions to the analysis of options markets and performing a thorough empirical evaluation of the issues using UK data. Furthermore, recent financial crises provide a fascinating opportunity to analyse investor behaviour during periods of extreme market pressure and to examine whether options markets are able to reveal any information that asset markets do not.

The four pieces of empirical work presented in this thesis aim to contribute to the understanding of investor behaviour in options markets and any implications that this behaviour has for future market volatility and returns.

Chapter 3 provides insights into the trading behaviour of options markets participants by examining the relative pricing and implied volatility of stock index put and call options traded on the London International Financial Futures Exchange before, during and after the dotcom bubble. The chapter identifies important issues which are analysed in depth. The subsequent results and their interpretation provide key insights into investor behaviour.

Chapter 4 builds on the analysis in chapter 3 in terms of implied volatility before during and immediately after the financial crisis of 2007/8. First the relationship between volatility indexes across international boundaries is examined by performing a variety of econometric tests on the VIX and VFTSE. The volatility forecasting ability and return predictability of volatility indexes is then tested. A useful contribution of this chapter is the construction of a unique volatility index which captures at-the-money implied volatility of FTSE100 index options from 2006, 2 years prior to the introduction of the VFTSE index. This permits *ex post* analysis of volatility and return behaviour from an *ex ante* perspective.

Chapter 5 focuses on the volume of trading and open interest observed during the 2007/8 financial crisis. The highlight of this analysis is an examination of the trading behaviour of options market participants in response to individual changes in return (or return innovations) compared with that in response to a series of consecutive returns of the same sign. Important insights are discovered which conform to the frequently observed behavioural biases of conservatism and the representativeness heuristic.

Chapter 6 completes the empirical analysis by testing for momentum and short-run overreaction effects before, during and after the 2007/8 financial crisis. It is hypothesised that price pressure is an important parameter in option pricing but that, in the short-run, options market traders overreact to a relatively small number of days' information if it is perceived to be of a large magnitude.

These four empirical chapters together provide a consolidated investigation and provide insights into trading behaviour in the UK options market that should be of interest to academics and practitioners. The results and their implications are summarised in Chapter 7 alongside suggestions for further research.

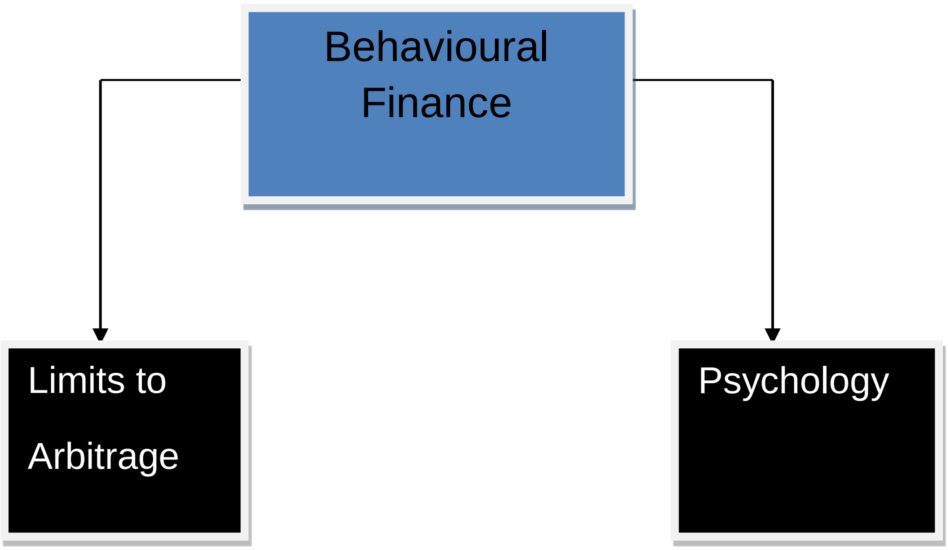
Chapter One

Behavioural Finance: Past, Present and Future

1.1 Introduction

In order to acquire familiarity with behavioural finance it is important to appreciate that the paradigm is founded upon two key building blocks, limits to arbitrage and psychology. Figure 1.1 identifies a number of important components of these building blocks.

Figure 1.1 Building Blocks of Behavioural Finance



- Miller 1977

- Shleifer & Vishny, 1997

- Shleifer, 2000

- Lamont & Thaler, 2003

- Barberis & Thaler, 2002

- Prospect Theory, Representativeness

(Kahneman & Tversky, 1979)

- Loss aversion

(Tversky and Kahneman, 1974, 1991)

- Conservatism

(Edwards, 1968)

- Noise

(Black, 1986)

- Biased self-attribution (Daniel, Hirschleifer & Subramanyam, 1999, Barberis, Shleifer & Vishny 1998)

- Framing, Anchoring, Regret

(Tversky and Kahneman, 1974)

The task facing researchers in the field of behavioural finance is to provide insights into numerous market phenomena that are unexplained, or for which traditional explanations are deemed less than satisfactory, using aspects of human behaviour identified by psychology. These insights can then be used to facilitate analysis of the implications for financial markets and hopefully lead to improvements in financial decision-making and the predictions of financial models. One way to rationalise the study of financial decision-making with the assistance of theories and evidence borrowed from psychology, is to consider the participants in financial markets. It does not seem unreasonable to assume that agents operating within financial markets are as likely to be subject to the preferences, beliefs and biases prevalent in the rest of society. Moreover, it is the consequences of these psychological factors, particularly on the market prices and returns of financial securities, that have implications for the efficiency of financial markets. According to Shleifer (2000), behavioural finance abandons the traditional assumption of competitive financial markets populated by only rational agents and replaces it with competitive financial markets populated by both fully rational agents and others who may be biased, stupid or confused. When these different categories of agent interact on a daily basis, security prices and returns are affected to such an extent that it seems unlikely that market efficiency will hold. It is the recognition of the human element in the decision making process that permits behavioural finance to offer explanations for a number of financial phenomena.

This chapter begins with a review of the concept of efficient markets complemented by a discussion of the key building blocks of behavioural finance. In addition it is important to include some definitions of concepts borrowed from psychology supplemented by an exploration of their relationship with the financial decision-making process. Subsequent discussion focuses on the challenges, both theoretical and empirical, faced by market efficiency and some of the behavioural explanations proposed for apparent inefficiencies. The chapter will conclude by suggesting some possible future directions for research in behavioural finance.

1.2 The Efficient Markets Hypothesis

The efficient markets hypothesis (EMH) is one of the cornerstones of modern finance and is a key component of traditional approaches to asset pricing. EMH is among the most widely tested hypotheses in financial economics with much of the early empirical work reviewed by Fama (1976).

According to EMH, an average investor will be unable to devise strategies to consistently outperform the aggregate market. As a consequence, the vast amounts of time and effort that investors devote to analysing, picking and trading securities is unnecessary. For more than ten years following its conception a substantial body of empirical evidence was published which was broadly supportive of EMH. More recently, the theoretical foundations of, and empirical support for EMH have been seriously challenged. For example, arbitrage is likely to be much less effective than supporters of EMH had previously assumed. The behavioural finance perspective is that the conclusion of efficient markets is incorrect, as the assumptions which underpin it are unrealistic. Although from the perspective of Friedman (1953) this is, of itself, not problematic.[2] Nevertheless, under conditions of limited arbitrage, there can be systematic and significant deviations from market efficiency which are likely to persist for long periods of time.

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[2] Friedman (1953) notes that assumptions in economics are necessary components of important and significant hypotheses. Furthermore the most significant hypotheses are likely to have the most unrealistic assumptions. The assumptions only need to be sufficiently good approximations in order to see whether the hypothesis or theory produces sufficiently accurate predictions.

The challenge for proponents of behavioural finance is to explain the evidence that, from the EMH perspective, appears to be anomalous and to generate predictions that can be supported by the data.

1.2.1 Theoretical Basis of the Efficient Markets Hypothesis

According to Shleifer (2000), the theoretical case in favour of EMH is founded on three central arguments each of which rely on progressively weaker assumptions:

(i) Financial markets are populated by rational investors who value securities rationally. That is, each security is valued according to its expected future cash flows which are discounted according to risk characteristics. The arrival of good news rapidly increases the security price while the arrival of bad news is quickly reflected in a price reduction. Such adjustments assume that new information is rapidly impounded in security prices. An implication of smoothly operating markets populated by rational investors is that it is impossible to consistently earn abnormal risk-adjusted returns. An efficient capital market is the outcome of equilibrium in competitive markets populated by fully rational investors.

(ii) In response to this argument it is perhaps difficult to support the notion that all investors value all securities rationally all of the time. Supporters of EMH propose that trades of irrational investors are random and consequently will not significantly affect prices. Where large numbers of irrational investors trade randomly their trades will cancel each other out, provided their trading strategies are uncorrelated. The outcome is that prices settle at, or close to their fundamental values. A limitation of this argument is that it relies crucially on an absence of correlation in trading strategies.

Shleifer notes that psychological evidence indicates that people do not deviate from rationality randomly, instead most deviate in the same way. Rather than trading randomly with each other many investors try to buy the same securities or sell the same securities at approximately the same time. If noise traders behave socially by following each other's mistakes, by listening to rumours or by imitating their compatriots then correlated trading becomes particularly severe. Investor sentiment is a reflection of the similar errors of judgement made by a large number of investors as opposed to random, unrelated errors. The literature on collective behaviour is reviewed in greater depth later in this chapter.

(iii) If irrationality is not random and traders engage in collective behaviour, then their trading strategies will be correlated. Supporters of EMH argue that irrational traders will be met in the market by rational arbitrageurs whose trades eliminate the irrational component of prices. As long as the assumption of unlimited arbitrage holds, a case can be made in support of EMH. Arbitrage may be defined as "a trading strategy that takes advantage of two or more securities being mispriced relative to each other" (Hull 2009, p773). For example, a stock that is overpriced in a market relative to its fundamental value because of correlated purchases by irrational investors will represent a bad buy. In this case the price of the stock will exceed the present value of its risk-adjusted future cash flows. Arbitrageurs will sell or short-sell this stock and hedge by simultaneously buying other 'essentially similar' securities. An arbitrage profit is made when the prices converge. The activities of competitive arbitrageurs will rapidly force the price of the overpriced security down to its fundamental value. Arbitrageurs will adopt a similar strategy when encountering underpriced securities and in the process eliminate the mispricing. Thus, even when some investors are not fully rational and their behaviour is correlated, provided close substitutes for securities are available, arbitrage will ensure they are priced according to their fundamental values. The availability of perfect substitutes to hedge out fundamental risk is central to the effectiveness of arbitrage.

If irrational investors purchase overpriced and sell underpriced securities the returns they earn will be lower than those earned by passive investors and arbitrageurs. It follows that they will eventually lose money and consequently their influence on the market will diminish or disappear entirely. The outcome is that mispricings will be temporary and efficiency will hold.

1.2.2 Empirical Support for the Efficient Markets Hypothesis

The vast majority of empirical evidence produced in the 1960s and 1970s supported the efficient markets hypothesis. There are two broad predictions of EMH that form the basis of empirical analysis:

(i) Security prices should react quickly and accurately to information – those who receive delayed information, for example in the financial press or company publications, should not be able to earn abnormal profits by trading on the basis of this information. If this is the case then price adjustments will be accurate on average. Prices should not overreact or underreact and there should not be price trends or reversals after the initial impact.

(ii) Prices should not move in the absence of news about the value of the security.

This means that earning consistent superior returns after an adjustment for risk should be impossible. Clearly, earning, on average, a positive cash flow from stale information does not necessarily indicate inefficiency, it could merely be compensation for bearing risk. It follows that in order to test for efficiency there is a problem identifying and quantifying the risk of a particular investment. A popular method is to utilise a model of risk and expected return such as the Capital Asset Pricing Model (CAPM) developed independently by Sharpe (1964), Lintner (1965) and Black (1972). Occasionally research has uncovered an opportunity to earn consistent abnormal profits as a result of trading on the basis of stale information. Critics have generally responded by identifying a model that reduces the positive abnormal cash flow to fair compensation for risk.

Fama (1970) formalised EMH by presenting three levels of efficiency; weak, semi-strong and strong. If a stronger level of efficiency holds then lower levels automatically hold although the converse is not true.

Weak form efficiency states that investors cannot earn consistent abnormal risk-adjusted returns by trading on the basis of past prices. If markets are weak form efficient there will be no repeating patterns in prices rendering technical analysis futile.

Semi-strong form efficiency states that investors cannot earn consistent superior risk-adjusted returns from using publicly available information. Once information is in the public domain it will immediately be impounded into prices meaning it is already too late for fundamental analysts to trade profitably.

Strong form efficiency requires that an investor cannot earn consistent abnormal risk-adjusted profits by trading on inside information. Strong form EMH states that this holds because inside information quickly leaks out and is incorporated into prices. Most research recognises that there may be profitable insider trading.

The following section summarises some important early evidence that is broadly supportive of EMH.

Fama (1965) found that stock prices from the Dow Jones Industrial Average approximately followed random walks. Consistent with the weak form of EMH, there appeared to be no systematic evidence of profitability of 'technical' trading strategies. Fama, Fisher, Jensen and Roll (1969) used event studies to analyse stock splits on the New York Stock Exchange. They investigated whether company stock prices adjust immediately to news or if the adjustment takes place over a period of days and produced evidence to support semi-strong form efficiency. Event studies can be used to evaluate the impact of any corporate news event on security prices. Keown and Pinkerton (1981) examined the share price of targets for takeover bids and noted that they begin to rise prior to the announcement of the bid as news of the possible bid leaks out and is incorporated into prices. Share prices then jump on the date of the public announcement to reflect the takeover premium offered to target firm shareholders. This is not followed by a continued upward trend or a downward reversal as all information is impounded into price by the day following the announcement. The results are presented as consistent with semi-strong form efficiency as prices adjust rapidly to the news.

Scholes (1972) analysed the implication of EMH that security prices should not react to irrelevant or non-information. Scholes employed the event study methodology to evaluate how share prices react to sales of large blocks of shares in individual companies by major shareholders. This analysis also directly addresses the issue of availability of close substitutes for individual securities, i.e. a security (or portfolio) with very similar cash flows in all states of the world, and therefore with similar risk characteristics to those of a given security. As noted earlier, the existence of close substitutes is essential to the effectiveness of arbitrage. Given the availability of close substitutes, investors should be indifferent as to which shares, in the same risk class, to hold. If large blocks of shares are sold there should not be any material impact on the share's price. The price should be determined by the share's value relative to that of its close substitutes rather than by supply. Scholes identifies relatively minor responses of share price to block sales. These are attributed to the possible, albeit small, adverse news signal provided when large blockholders decide to sell their shares. This result is consistent with the prediction of EMH that share prices do not react to non-information and highlights the willingness of investors to adjust their portfolios to absorb more shares without a large influence on share price.

1.3 Behavioural Finance Building Block One: Psychology

The objective of this section is to examine the contribution of psychology as a key behavioural building block and to consider important applications in finance. The deviations from rationality that contribute to the type of mispricings arbitrageurs would like to exploit are identified within the discipline of psychology. Psychologists provide evidence on the biases that cause irrational behaviour and categorise them as either beliefs or preferences.

The discipline (or sub-discipline) of cognitive psychology involves analysis of the ways in which people gather, process and store information in order to understand their surroundings. In other words how people think, perceive, remember and learn. The key emphasis of the field is on how understanding their environment affects how people behave. Cognitive psychology is a very broad field with numerous applications so this discussion will be confined to aspects pertinent to the understanding of financial decisions.

It is generally accepted in the field of psychology that people perceive and understand information in ways which are biased and limited. For example, Reber (1995) identifies perception as being determined by attention, constancy, motivation, organisation, set, learning, distortion, hallucination and illusion. How people understand their environment is shaped by simple abstractions known as mental frames. They choose what they want to believe and once these frames are formed they can be highly resistant to change.

Heuristics, in the cognitive context relevant to behavioural finance, refer to the various methods people use to solve problems, make decisions and form beliefs. Put simply, they are rules of thumb that have been learned over time and guide the way in which decisions are made and problems solved. Heuristics are likely to influence financial decision-making as it often occurs under incomplete information, when time is limited or where problems are highly complex. Examples of heuristics that will feature prominently in this study are framing, anchoring and representativeness.

The beliefs and preferences considered most important to finance are discussed in the following sections.

1.3.1 Beliefs

1.3.1.1 Framing

Framing is a key aspect of prospect theory which will be discussed in greater depth in the section on preferences. Framing is a cognitive bias that arises because of the way in which a decision or problem is presented to the decision-maker. The way questions are asked influences the answers that people give. Individuals are all sensitive to the context in which something is presented hence framing can result in significant shifts in preferences. If investors make different choices depending on how a given problem is presented to them this is a clear deviation from rationality. For example, Bernartzi & Thaler (1995) note that investors allocate a greater proportion of their wealth to stocks and a lower proportion to bonds when they observe an impressive history of long-run stock returns relative to returns on bonds as opposed to when they only observe volatile short-run stock returns.

1.3.1.2 Overconfidence

The discussion in the previous section indicates that individuals may be biased when forming their beliefs. One important type of bias is overconfidence which is apparent when people put too much faith in their own judgements. For example an individual investor may display overconfidence in his ability to pick stocks that will appreciate in value. Evidence of overconfidence is of particular importance in financial economics.

Generally overconfidence has been demonstrated in experimental studies where people assign confidence intervals to quantitative estimates which are too narrow. Furthermore, people make poor estimates of probabilities. According to Fischoff, Slovic and Lichtenstein (1977), events assigned a probability of one occur on average 80% of the time and events assigned a probability of zero occur on average 20% of the time.

In order to further examine overconfidence it is important to identify the key characteristics of overconfident people. Nofsinger (2010) notes that they overestimate their knowledge, underestimate risks and exaggerate their ability to control events. To highlight overconfidence in decision-making Nofsinger argues that the selection of financial securities is a very difficult task yet it is typical of the type of task in which people display the most overconfidence.

People are most overconfident when they feel that they have some control over the outcome of what in many cases are completely uncontrollable events. This is known as the illusion of control. If this psychological factor were applied to investors the expectation is that overconfident investors will believe that stocks they own will perform better than ones they don't own. Investors expect that the stocks they have purchased will provide them with an above average return. There is a perception that the ownership provides a degree of control. The hypothesis that people believe they exercise a degree of control over uncontrollable events can be examined by considering the behaviour of online investors.

Daniel, Hirshleifer and Subrahmanyam (1998) assert that the self-attribution bias is a significant contributor to overconfidence and can contribute to momentum in asset prices. Investors need to gather and analyse information prior to making buy and sell decisions. Overconfident investors will overstate the accuracy of this information and their ability to accurately interpret it particularly when they have enjoyed prior success. Self-attribution exacerbates overconfidence due to the tendency of investors to attribute success to personal skill but failure to bad luck. Furthermore, individual investors will be much more prone to overconfident behaviour in bull markets because they will have been likely to have received a stream of positive returns. The opposite is true in bear markets where negative returns would be the norm.[3] Overweighting one's own ability relative to publicly availability will inevitably lead to poor decisions and an increase in the quantity and magnitude of errors.

The evidence regarding overconfidence is focused on the implications for investor behaviour. In particular excessive trading and risk taking are prime examples. In

[3] See Hilary and Menzly (2006) for a study of analyst predictions following prior success.

examining whether overconfidence is problematic the ultimate indicator is performance.

The traditional finance assumption of rationality will be seriously challenged if evidence of excessive trading is produced. If investors are truly rational there should be very little trading on stock markets. If all investors are rational, and they know that all other investors are rational, then investor X should be reluctant to buy a security from investor Y if investor Y is willing to sell. Furthermore every purchase or sale of a share incurs transactions costs. Hence a consequence of excessive trading is that excessive transactions costs are incurred which seriously erode net returns. Despite compelling reasons not to overtrade, the volume of trading on global financial markets is extremely high. It is evident that individual and institutional investors trade much more than can be justified than if they were truly rational.

Barber and Odean (2000) find that, once trading costs are taken into consideration, the average return earned by investors is substantially below the return on standard benchmarks. They identify transactions costs incurred by excessive trading as responsible for eroding a significant proportion of returns, with the remainder attributed to poor security selection. Both causes are consistent with the notion of overconfident investors. In an earlier study Odean (1999) notes that the average return on stocks that excessively trading investors buy, in the following year, is less than the average return on the stocks that they sell. In the year following the trades the stocks sold outperformed the stocks bought by 5.8%. It appears that the more overconfident the investor is the more they will trade and will earn lower average returns as a result.

Barber and Odean (2000) explore the relationship between high turnover[4] and portfolio returns. An investor who receives good information and is proficient at interpreting it should be able to achieve high returns. Certainly the returns should be better than those from a simple buy-and-hold strategy once trading costs have been taken into account. If they do not have superior information or superior ability then the high trading costs incurred mean they will, on average underperform the simple buy-and-hold strategy.

Barber and Odean looked at a sample of 78,000 household accounts over the period 1991-96 and sorted these into 5 groups according to turnover. Each group contained 20% of the sample and were found to achieve the same annual gross returns, 18.7%. Hence the high turnover investors did not achieve additional returns for their additional efforts. This is further exacerbated because commissions need to be paid when stocks are bought and sold, increasing the aggregate costs for high frequency traders. Hence the net returns are much lower for the high turnover group (11.4% on average) than for the low turnover group (18.5% on average). This finding is illustrated in terms of money in Table 1.1.

Table 1.1 Net Returns by Stock Turnover

Group	Return	Investment	After 5 Years
Low Turnover	18.5%	£10,000	£23,366
High Turnover	11.4%	£10,000	£17,156
Difference	7.1%		£6,210

[4] Turnover is the percentage of stocks in a portfolio that changed during a year.

The destructive impact on returns leads Barber and Odean to state that trading is hazardous to your wealth!

Psychologists have found that men are more overconfident than women in tasks that are seen as masculine. Managing finances is categorised as masculine, indicating that men will be more overconfident about their ability to make investment decisions. Consequently it is logical to expect that they will trade more. Barber and Odean (2001) test this hypothesis by investigating the trading behaviour of 38,000 households through a large discount brokerage firm between 1991 and 1997. They examined the stock turnover of single and married men and women and discovered that single men trade the most (85%), then married men (73%), married women (53%) and single women (51%). This finding demonstrates that men tend to be more overconfident, trade more and consequently earn lower returns on average than women. The work of Barber and Odean in this field is limited in the sense that it is restricted to small investors.

Statman, Thorley and Vorkink (2006) examine the aggregate stock market for evidence of overconfidence. For an aggregate market to exhibit overconfidence many investors need to be overconfident at the same time. Under the assumption that many investors attribute their high returns to their individual skill and become overconfident, investors would be most likely to be collectively overconfidence following or during a sustained aggregate market increase. If, as a consequence, they trade excessively it will appear as a significant increase in trading volume on stock exchanges. Statman, Thorley and Vorkink demonstrate that, over a 40 year period, high trading volume follows months where there have been high returns. Furthermore low trading volume follows months with market declines. This evidence supports the notion of overconfidence in the aggregate stock market.

A notable feature of overconfident investors is that they are likely to misinterpret their degree of risk exposure. A key pillar of traditional finance is portfolio theory which highlights the risk return trade-off and the benefits of diversification. It is assumed that rational investors will seek to maximise returns for the lowest possible risk. Conversely the portfolios of overconfident investors will be relatively undiversified and include a relatively large proportion of high-risk stocks. Hence their portfolios will be highly volatile and have high betas.

Barber and Odean (2000) analyse the portfolios of investors for evidence of the characteristics of overconfidence. They find that the portfolios held by single men are the most volatile, have the highest beta values and tend to have the highest concentration of stocks of small companies. Consistent with their findings on excessive trading, this was followed by married men, married women and single women. Where groups were sorted by turnover, the high turnover groups included the largest number of small firm stocks and had the highest betas compared with the low turnover group. This finding is presented as evidence that investors who trade the most are the most susceptible to underestimation of their risk exposure. Again this study is limited to the extent that it only considers relatively small investors.

Literature on the causes of overconfidence places particular emphasis on knowledge and information. Individuals may believe that a greater quantity of information improves their ability and hence their decision making. This aspect of human behaviour is generally referred to as the illusion of knowledge. The impact of information and perceived knowledge is highlighted in the evolution of trading from telephone to on-line which appears to increase overconfidence. The internet provides a vast amount of historical and current information which may lead individual investors to believe they are better informed and more able to properly interpret the information than they really are. Much of their additional information arrives in the form of analyst tips via newsgroups and chat rooms. However it is not always clear which of these tips are expert recommendations.

Dewally (2003) analyses recommendations posted on the message boards of internet newsgroups and finds that stocks recommended as a buy under a momentum strategy underperform the market by more than 19% in the subsequent month. However, those recommended under a value strategy outperform the market by more than 25% the next month. Overall, trading on the basis of these tips does not produce returns significantly different from the market in general.

Tumarkin and Whitelaw (2001) find that when positive stock recommendations are posted the volume of trading increases but the increase in volume is not associated with a rise in returns. This is interpreted as evidence that positive recommendations appear to make investors overconfident.

In aggregate the evidence is consistent with investors who are prone to the illusion of control. In particular, the availability of online trading allows investors to easily gather information and use this to inform their own buying and selling decisions. This active participation engenders a sense of familiarity which in turn strengthens the perception of control. Furthermore online trading came to prominence during the bull market of the late 1990s. The associated early positive outcomes are likely to reinforce the illusion of control.

Barber and Odean (2002) analyse the trading patterns of 1,607 investors who switched from telephone-based to internet-based trading. They note that investors who switched often earned high returns prior to switching and hence were likely to possess an increased level of confidence. Barber and Odean discover an immediate increase in the turnover of these traders from 70% to 120% before it settled at 90%. Increased turnover was associated with poorer performance with average annual returns falling from 18% to 12% which represented an underperformance relative to the aggregate the market of 3.5%. This evidence clearly suggests that investors who enjoyed past successes became overconfident prior to switching to online trading. Internet trading may have made them more overconfident for the reasons already discussed. The outcome is excessive trading and reduced returns. The interpretation of these results seems rather narrow as it may be that availability and novelty are important determinants of the surge in trading activity rather than just overconfidence. This aspect is overlooked in Barber and Odean.

1.3.1.3 Optimism and Wishful Thinking.

Psychologists argue that people are over optimistic in that they hold generally unrealistic views of their abilities and prospects. Associated with this type of belief is a systematic planning fallacy. The most clear and common example of this fallacy is when individuals regularly predict that tasks will be completed much more quickly than is realistic or is actually realised. Similarly, people hold unrealistically optimistic perspectives of their personal prospects and abilities.

Optimism is an important factor in a number of aspects of investor behaviour. For example an optimistic investor may believe that their ability in security selection makes a bad outcome for their portfolio less likely than is realistic. This can result in insufficient analysis of investments and a tendency to disregard or downplay negative information. For example, when negative news is released about a firm the optimist, with a personal stake, maintains the belief that the firm is a good investment.

An early theoretical challenge to EMH was presented by Miller (1977) who argued that, under conditions of uncertainty, investor opinion on the returns from holding risky stocks will diverge. Where short-selling is limited the price of a stock will be driven by the most optimistic investors; those who choose to purchase the stock and hold it in their portfolios. If pessimistic investors cannot short sell then the stock is likely to be overpriced. Miller argues that divergence of opinion will be an increasing function of risk and, as a consequence, higher risk securities will offer lower returns particularly where information is scarce. Such a finding is in direct contradiction to EMH and the CAPM.

Hong and Stein (1999) apply Miller's theory to firm size. They note that, where there is difference of opinion, optimistic investors drive prices, particularly for small firms, due to incomplete information. Optimistic investors value stocks much higher than pessimistic investors. As the latter are short sale constrained they merely exit the market. This means that arbitrageurs can only trade with optimistic investors but cannot easily establish the degree of mispricing. Large firms typically have more analyst coverage than small firms, hence more complete information is easily available to all market participants. The outcome is that large firms are less likely to be mispriced (or the mispricing less severe) where there is difference in opinion.

Investors who purchase stocks whose price is driven up by optimism will normally lose as the optimism unwinds. This was particularly evident in the dot-com bubble which burst in 2000. Such rampant optimism is often referred to as irrational exuberance.

1.3.1.4 Representativeness

Representativeness is essentially a bias where individuals form views according to stereotypes. Kahneman and Tversky (1972) define representativeness as a bias towards formulating expected outcomes from a distribution of impressions. In other words an expected outcome is biased by the subject being representative of a particular class.

Representativeness is highlighted by Tversky and Kahneman (1974), who argue that when people attempt to establish the probability that a set of data A, is generated by a model B, or that an item A belongs to a particular class B, they tend to employ the representativeness heuristic. People will evaluate the probability by the extent to which A appears to reflect the key characteristics of B. Representativeness can generate a bias known as base rate neglect where the probability of an event is downplayed in favour of more easily accessible information.

Representativeness will be considered further in later chapters hence only a brief overview of applications to finance is necessary here. For example, Barberis, Shleifer and Vishny (1998), note that representativeness is prevalent in financial markets where individuals find trends in data too readily and extrapolate these into the future.

Representativeness can lead to sample size neglect where individuals believe that a small sample is representative of the parent population. For example, if a financial analyst makes a series of accurate positive stock recommendations then investors will tend to believe that this is a talented analyst who is able to predict the market. They are likely to reason that a run of successes is not representative of a bad analyst and the analyst will be likely to confirm this view.

A further relevant application is a bias known as the gambler's fallacy effect. For example if a stock index has fallen on four successive days investors may believe that a rise in the index is due.

1.3.1.5 Conservatism

Conservatism is another bias which will be considered in greater depth in later chapters, particularly when discussing the reconciliation of underreaction and overreaction. Conservatism is evident in situations when people put too much weight on their initial beliefs relative to available sample evidence. If people have a particular view or belief they may be resistant to alter it even when faced with overwhelming evidence to the contrary. The effect of conservatism in finance is that market participants react too little to the available data and place too much reliance on their prior beliefs.

1.3.1.6 Confirmation Bias

Confirmation Bias refers to a situation where people actively seek information that confirms their views. Furthermore, once people have formed a hypothesis they sometimes misread additional contradictory evidence as actually being in their favour. For example an investor may observe one stock analyst that confirms his opinion and four who disagree. If the investor suffers from confirmation bias he may give more weight to the opinion of the first analyst than to the opinions of the other four.

1.3.1.7 Anchoring

Anchoring occurs when people begin with a, possibly arbitrary, initial value when forming estimates then adjust away from it. Evidence shows that people anchor too much on the initial value. For example the purchase price of a stock or a fairly recent high price may affect investor decision making. This is particularly important in situations of uncertainty. People will try to find an initial value to anchor to and use this to provide a basis for their estimate.

1.3.1.8 Cognitive Dissonance

When faced with evidence that their beliefs may be incorrect or inaccurate people experience mental conflict. In order to resolve this conflict they will go through a series of mental processes. The brain attempts to ignore or downplay the information that conflicts with the individual's established beliefs. Goetzmann and Peles (1997) quiz professional investors about returns on their previous year's investments in mutual funds and find that they over-estimate past returns by 3.40% on average and over-estimate their performance relative to the market by 5.11%. This finding is presented as evidence that investors want to believe they made good investment decisions. If there is evidence to the contrary the brain filters it out and alters recollection. Goetzmann and Peles argue that cognitive dissonance explains mutual fund inertia. Investors in poor performing funds filter out the previous poor performance of the mutual fund and fail to switch to better performers. The implication for financial markets is that cognitive dissonance of investors weakens a constraint on managerial performance.

1.3.1.9 Memory Bias

Memory Biases are apparent in cases where more recent and hence more salient events will carry greater weight. Investor estimates and consequently their behaviour may be distorted where not all memories are equally retrievable or available. For example, consider an investor who purchases two stocks, X and Y, at the beginning of the year for £20 each. X falls slowly over the year to £15; Y remains at £20 for most of the year then falls dramatically to £16 in the last few days of the year. Although the investor lost more on X they are likely to feel more pessimistic about Y because the pain of the sudden loss is salient and emotionally painful.

1.3.2 Preferences: From Expected Utility to Prospect Theory

The analysis of preferences is focused on how individuals make decisions under conditions of uncertainty.[5] Traditionally, investment decision making under uncertainty involves investors who either accept that they have incomplete information and make the best decisions they can, given their information set, or investors who seek out as much relevant information as possible prior to making decisions.

Any discussion of preferences requires an understanding of prospect theory which was developed by Kahneman and Tversky (1979, 1986). This involves an appreciation of how investors evaluate risky gambles. Prospect theory was developed in response to experimental evidence, which suggested that investors systematically violate expected utility theory when choosing from among risky gambles. The apparent weaknesses of expected utility theory, which is the orthodox approach to preferences, provide one of the key drivers of the behavioural approach to financial decision-making. Recent work in behavioural finance argues that some of the insights psychologists have drawn from violations of expected utility are central to understanding a number of financial phenomena.

[5] Formally risk and uncertainty can be characterised as a situation when there are more potential outcomes than can actually occur. However a situation of risk has a probability distribution of outcomes whereas no probabilities can be assigned under a situation of uncertainty. In the finance literature it is not uncommon to observe the two terms used interchangeably.

The starting point for expected utility theory is a fair gamble or lottery where the utility offered is a weighted average of expected outcomes. This can be used to produce a generalised utility function:

$U = L(o_i, p_i) = L(o_{1,}\ o_2\text{.....},\ o_{n;}\ p_1, p_2\text{....},\ p_n)$

Where o_i are potential outcomes with associated p_i probabilities, i = 1 ... n.

Expected utility theory represents the utility of expected outcomes with respect to the best and worst possible outcomes. Hence it is possible to construct an ordering of weighted expected outcomes with associated probabilities. Expected utility is individual to each investor therefore the probability weights attached to each outcome are subjective. Clearly these can be difficult to formulate and are subject to considerable uncertainty. The standard utility function for a risk-averse investor will be increasing in wealth but at a decreasing rate. Expected utility is concerned with how decisions under uncertainty should be made as opposed to how they actually are made.

In response to the fact that probabilities are rarely objectively known, Savage (1954), developed subjective expected utility. The advantage of this is that it can accommodate ambiguity aversion (Ellsberg, 1961), which can be described as a dislike of vague uncertainty where information that could be known is not. In fact people dislike subjective uncertainty more than they dislike objective uncertainty. In essence, the preferences of individuals are weighted by their subjective probability assessment. Investors may display ambiguity aversion where they feel less competent in assessing relevant probabilities when compared with others who are more competent in that particular area or when compared with investments in which they have more expertise.

A significant challenge to expected utility theory is the view that it does not properly describe how investors actually make decisions. Financial decision making often violates the von Neumann-Morgenstern axioms which underpin the notion of rationality. Some key assumptions relevant to investor behaviour are:

- Alternative investments can be ranked.
- The dominant investment is preferred; i.e. the investment which offers the best outcome in all states of the world or in most states of the world and no worse in the remainder.
- Irrelevant alternatives are ignored in the choice process.
- Investors rank alternatives continuously as a linear combination of the best and worst outcomes.
- Investors care about outcomes and probabilities. How they are bundled or presented does not affect expected utility.

Problems with expected utility are highlighted by some famous paradoxes. For example the Ellsberg paradox demonstrates a violation of the irrelevance axiom by illustrating that the evaluation of a prospect can be seen to depend upon its packaging with an irrelevant alternative (Ellsberg, 1961). The Allais paradox (Allais, 1953) sees the reversal of preferences between alternatives by the majority of individuals when they are presented to the decision maker in a different way thus highlighting the difficulty expected utility theory has in explaining observed choices under uncertainty.

Prospect theory concerns decision making under uncertainty and provides an alternative to the conventional economic model. In common with expected utility theory prospect theory proposes that the value of a risky alternative is the product of a function of outcome values and their probabilities. However unlike under expected utility, both functions are psychological to the extent that they are matters of taste. The objective of prospect theory is to attempt to capture the individual's attitudes to risky gambles as parsimoniously as possible.

Prospect theory was motivated by a number of observed violations of expected utility theory. Mental frames, which can be manipulated with the effect of changing an investor's decision, are the key drivers of the observed violations.

A simple framing problem posed by Tversky and Kahneman (1981) is as follows:

The government is preparing for a deadly outbreak of Asian flu from which it is estimated that 600 people will die. A sample of students are asked which course of action they support:

Action A offers a vaccine which can save 200 lives

Action B offers a vaccine which will stop anyone dying at all if it works (which it will do with a probability of 1/3) but will cure no one if it does not work.

A second group of students are asked which action they support given the same health threat:

Action C accepts that 400 victims of the flu will die.

Action D offers a vaccine which has a probability of 1/3 of curing all victims, but if it doesn't work will result in all 600 victims dying.

In the first case, given this choice, 75% of students asked selected programme A. The risk of all 600 victims dying appeared too tragic to be compensated by the hope that all would be saved.

In the second case 66% of students selected programme D. The potential death of 400 was sufficient to discourage most from selecting programme C even though it provides the same outcome as programme A. This is a clear illustration of framing effects as it demonstrates that it is how the question is asked as well as the question being asked which determines the answer. The notion of consistent ranking is clearly violated.

Under the prospect theory approach people seek to maximise a weighted sum of utilities. However the weights that they seek to maximise do not match the actual probabilities. Importantly, under prospect theory, the utilities are determined by a value function instead of a utility function.

According to Kahneman and Tversky people also suffer from a certainty effect where they tend to allocate zero weight to outcomes which are relatively unlikely but not impossible. Conversely, outcomes that are relatively certain, but not guaranteed, tend to be allocated a weight of one. In other words, they behave as if they believe highly improbable events to be impossible and highly probable events to be certain. In addition to overweighting small and large probabilities, moderate probabilities are underweighted.

The concern of prospect theory is to model how decisions actually are made. It posits that it is gains and losses relative to some meaningful reference point, rather than final wealth itself, which determine utility or value. Thus people value changes as opposed to states. This is in marked contrast to the expected utility focus on alternative values of final wealth. A particular feature of investor behaviour is the tendency to evaluate individual gambles independently from other areas of wealth. For example, a risky investment will be evaluated as if it were the only gamble faced by the investor, rather than considering its merits as an addition to the risky investments already held.

Another principle of prospect theory is that losses hurt more than gains please the investor. Individuals are considerably more concerned about gains and losses relative to current wealth than they are about maximising the expected utility of wealth.

The prospect theory value function is defined over gains and losses around a reference point. The reference point provides a benchmark and is determined by the subjective feelings of the individual. The attitude towards risk changes around the reference point from concave for gains to convex for losses. Loss aversion is illustrated by the slope of the value function which is steeper for losses than it is for gains.

Figure 1.2 Loss Aversion

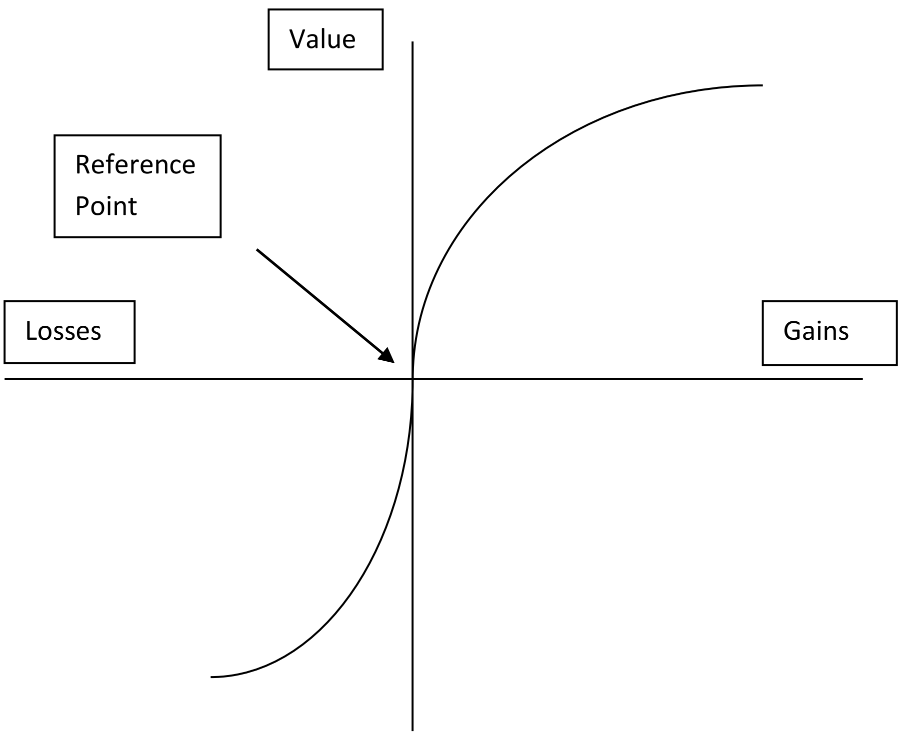

Figure 1.2 illustrates that a loss is more painful than a gain of equivalent magnitude is pleasant. Investors' loss aversion is clearly demonstrated by their greater sensitivity to losses as opposed to gains. The investor's degree of risk aversion appears to increase with the size of a gamble to the extent that they will be extremely risk averse over large stake gambles.

Shefrin and Statman (1985) applied prospect theory to investor behaviour. They referred to the predisposition to retain stocks that had incurred losses and sell stocks that had made gains as the disposition effect. The disposition effect is consistent with the prediction of prospect theory that people dislike incurring losses much more than they enjoy making gains. Investors demonstrate an aversion to the feeling of regret and are willing to gamble in the domain of losses (relative to their reference point). Hence they hold on to losing stocks in the hope that they will recover, or the expectation that they will 'bounce back', and sell winning stocks to realise the gains. This is in contrast to Constantinides' (1983) tax-based explanation of disposition which was later rejected by Odean (1998) on the grounds that it fails to capture significant features of the data. Furthermore, his finding, that winners outperform losers following rebalancing, rules out private information as a possible explanation for the disposition effect. Odean's presents his findings as support for a prospect theory-driven disposition effect. Odean finds that small retail investors in particular are susceptible to the disposition effect and incur losses as a result. Shefrin and Statman argue that investors, even in the face of tax advantages, are reluctant to close a position at a loss. It appears that investors indulge in mental accounting when assessing individual investments.

Odean (1999) produced evidence to indicate that investors retain losing stocks a median of 124 days and retain winning stocks a median of 102 days. Furthermore

1.5 times as many gains are realised as opposed to losses. Odean found that the unsold losers earned a 5% return in the subsequent year whereas the sold winners earned returns of 11.6%. This indicates that the disposition effect results in sub-optimal strategies.

Locke and Mann (1999) investigate the behaviour of professional futures floor traders at the Chicago Mercantile Exchange during 1995. They find evidence that the futures traders display patterns which are consistent with the predictions of the disposition effect. This finding indicates that professional traders, as well as retail investors, exhibit behaviour consistent with the disposition effect.

Frazzini (2006) finds that the disposition effect contributes towards underreaction as the tendency of investors to realise gains suppresses share price and to hold on to losers props up share price. The underreaction effect is followed by post news drift.

Prospect theory may be presented in a dynamic setting by analysing repeated games where the perception of risk appears to change depending on prior outcomes. For example, Thaler and Johnson (1990) demonstrated that investors are more risk seeking following prior losses and more risk averse following prior gains. This finding indicates that losses are likely to be more painful following negative returns. This is referred to as a break-even effect as investors hold on to the possibility of recouping losses. Losses are likely to be less painful following positive returns. This result is generally referred to as the ‘house money’ effect as a greater willingness to gamble with money gained is evident (i.e. the House’s money). Barberis, Huang & Santos (2001) also investigate dynamic aspects of loss aversion and support the notion of a house money effect in financial markets. They conclude that recent gains in financial markets make investors less risk averse or more risk loving and recent losses make investors more risk averse.

The finding of a house money effect does not necessarily imply investor irrationality. Rather it may simply be a prudent update on confidence in the investor’s own ability or a mechanism to protect against losses that cannot be funded or that are too damaging.

The disposition effect highlights attitudes to risk as a key fundamental area in which investors deviate from rationality. Investments are assessed on the basis of gains and losses relative to some reference point which may vary according to the situation rather than on the basis of attainable final wealth. Investors display loss aversion and become much more risk seeking when faced with losses. However, when faced with large gains they become much more risk averse. The resulting behaviour is inconsistent with building wealth. Rational behaviour would involve selling loss making positions and holding on to profitable positions. Cashing in to preserve gains and holding on to loss making positions in the hope that the losses can be recouped can be interpreted as a clear illustration of irrational behaviour in financial markets. However, although prospect theory provides a plausible structure to analyse the disposition effect, the literature discussed so far does not provide a rigorous model for analysing investor behaviour.

Barberis and Xiong (2009) question the role of prospect theory as a cause of the disposition effect. They construct a model to analyse the trading behaviour of an investor with prospect theory preferences. Barberis and Xiong consider two implementations of prospect theory; to annual trading gains and losses and also to realised gains and losses. Their simulated trading strategy indicates that an annual gains and losses model fails to predict a disposition effect whereas a realised gains and losses model does predict a disposition effect. In fact, for some values of expected return and numbers of trading periods a reverse disposition effect is found. The key implication of the authors' findings is that investors distinguish between paper gains and losses and realised gains and losses. Prospect theory is found to predict a disposition effect when realised gains and losses are used because the investor feels the benefit of prospect utility at the point of sale. Barberis and Xiong's results are derived from an artificial data set where a riskless asset and risky asset both follow a binomial process.

Hens and Vlcek (2008) evaluate the role of prospect theory in the disposition effect by considering whether the effect is conditional on whether the stock was purchased or already held. Hens and Vlcek argue that the disposition effect cannot be explained by prospect theory if the investor were to purchase, rather than be endowed with the risky asset. Central to this argument is that, faced with the prospects of selling winners and holding losers, an investor would not have invested in the first place. The prospect theory argument rests on the assumption that the investor has bought the stock and therefore has not decided to end up in a situation where the disposition effect might occur. Hence prospect theory explains the disposition effect from an *ex post* perspective but not *ex ante*.

Hens and Vlcek construct a theoretical model to examine the *ex ante* and *ex post* disposition effect with particular focus on the myopic small individual investor. The model involves two consecutive portfolio choices. In other words the investor is required to buy the asset in the first period and makes the decision whether to hold or sell in the next. The authors find that investors who conform to the disposition effect would not have purchased the stocks in the first place. The implication is that prospect theory can explain the existence of the *ex post* but not the *ex ante* disposition effect. Furthermore, the strength of the *ex post* disposition effect is found to vary inversely with the degree of investor risk aversion and positively with the degree of downside risk of the underlying asset. Hens and Vlcek's model is limited in that it only considers a binomial case. For a more complete analysis the model will need to be applied to multiple risky assets. It would also be interesting to see how the model performs empirically.

Tversky and Kahneman (1992) propose cumulative prospect theory where the individual's attitude to risk is determined jointly by the prospect theory value function and cumulative probability. The outcome is that individuals are risk seeking for small probabilities of gains and risk averse for low probabilities of losses yet conform to the predictions of standard prospect theory when probabilities are high. However, where the inflection point sits is inexact. Barberis and Huang (2008) apply cumulative prospect theory to investor behaviour in financial markets by focusing on the probability weighting function. Investors can have homogeneous preferences and beliefs under cumulative prospect theory yet can hold different portfolios. Barberis and Huang introduce a small positively skewed security offering a return slightly in excess of the riskless rate of interest. Under cumulative prospect theory the security can become overpriced and earn a negative abnormal return. Some investors, who overweight tails, are willing to take large undiversified positions in the positively skewed security as it mimics a lottery-style gamble. At the same time it is difficult for other investors to exploit the overpricing due to risks in taking short positions in skewed securities. Barberis and Huang offer cumulative prospect theory as an explanation for the low long-term average returns on IPOs. IPOs are issued by relatively young firms with positively skewed returns. They often become overpriced and subsequently earn low returns yet still attract investors. Cumulative prospect theory also has applications to the pricing of put options and offers an explanation for the volatility smile, particularly in individual equity options with relatively low institutional ownership.

1.4 Behavioural Finance Building Block Two: Limits to Arbitrage

According to Barberis and Thaler (2002) behavioural finance presents the argument that arbitrage strategies designed to correct a perceived mispricing can be very risky even if the security seems wildly mispriced. This means that mispricings can remain unchallenged. Shleifer (2000) argues that ultimately, the theoretical case for efficient markets depends on the effectiveness of arbitrage. Shleifer states that in contrast to the neoclassical perspective, behavioural finance argues that in a real-world setting arbitrage is risky and, as a consequence, its effectiveness as an equilibrating mechanism is limited. Derivative securities such as options and futures normally have close substitutes even though arbitrage may require considerable trading. But the majority of equity and debt securities lack obvious substitutes. Thus, in the case of stocks and bonds, arbitrage may not enable price levels to be determined with any great degree of certainty. Figlewski (1979) and Campbell and Kyle (1993) indicate that arbitrage moves prices towards, but not completely to, fundamental value because risk-averse arbitrageurs are reluctant to take large arbitrage positions.

Under the traditional framework of rational agents and no market frictions a security's price will equal its fundamental value. However this rests crucially on the assumption that arbitrage is riskless. The behavioural finance approach posits that asset prices deviate from fundamental value as a result of the actions of traders who are not fully rational. Traditional finance offers the counter argument that rational traders will quickly eliminate these deviations. For arbitrage to operate efficiently deviations from fundamental value must create attractive investment opportunities which rational investors immediately accept and, as a result, correct the mispricing. However, even when an asset is significantly mispriced strategies designed to correct the mispricing can be costly and risky. This can make them unattractive and hence the mispricing is not corrected. The strategies rational traders are assumed to take under the traditional view are not pure arbitrage.

Barberis & Thaler (2002) pointed out that markets can be inefficient yet there are not necessarily excess risk-adjusted average returns available. If prices are right there is no free lunch but the absence of a free lunch does not imply that prices are right. Just because professional money managers are not able to consistently beat the market does not necessarily imply that markets are efficient. Barberis and Thaler argue that findings to this effect do not provide strong evidence of market efficiency.

The finding of no profitable inefficiencies does not mean that inefficiencies are unimportant. Ultimately we should be concerned as to whether resources are allocated to their most promising investment opportunities and that allocation is influenced by the accuracy of prices.

There are three key sources of risk faced by risk-averse arbitrageurs that limit the effectiveness of arbitrage: fundamental risk, noise trader risk and implementation costs.

Fundamental risk presents a significant deterrent to arbitrage where the arbitrageur bears unsystematic risk that news regarding the securities he is short in is unexpectedly good and that news regarding securities he is long in is unexpectedly bad. Fundamental risk occurs for example where a long position is taken in a particular stock and subsequent bad news is released about the company. The short position in the substitute position, which forms the other leg of the arbitrage strategy, fails to offset this as substitutes are rarely perfect. In practice they are normally very far from perfect which exacerbates fundamental risk. With imperfect substitutes arbitrageurs are operating 'risk-arbitrage' strategies which focus on the statistical likelihood, as opposed to the certainty, of convergence of relative prices. There can be additional risk if the substitute shares are also mispriced.

Noise trader risk (Black, 1986) concerns the possibility that the mispricing being exploited by the arbitrageur worsens in the short run. For example, pessimistic sentiment causing a stock to be undervalued may deepen in the short run causing the price to fall even further. The importance of noise trader risk should not be underestimated as it can result in early liquidation of arbitrageurs' positions, potentially incurring substantial losses. Most real world arbitrageurs are managing other peoples' money hence there is a separation of brains and capital. Investors without the specialised knowledge to evaluate the arbitrageurs' strategies will simply evaluate their returns. If the mispricing worsens in the short run then this will appear as negative returns and lead to the questioning of the arbitrageur's competence. If investors, as a result, withdraw their funds then arbitrageurs may need to prematurely liquidate their positions and the mispricing will persist. Also the fear of this scenario makes arbitrageurs less aggressive in combating mispricings. The situation can be exacerbated by creditors. If they observe the value of their collateral eroding they will call their loans. Because arbitrage is usually performance-based investors will withdraw funds from arbitrageurs with poor recent performance and allocate to those with better recent performance. Consequently arbitrageurs are likely to operate with short time horizons. However, performance does rest on the assumption that investor inertia is minimal.

Mispricing can then be reinforced by difficulties in raising new funds to exploit arbitrage opportunities. When positions are liquidated shares are sold below fundamental values because other arbitrageurs will be facing similar constraints. Arbitrage is also hampered by the need to sell securities short to hedge fundamental risk. Should the original owner of the shorted securities require them back, and no other alternatives are available, then the arbitrageur will be forced to close the position. This potential scenario again makes them more cautious. The outcome is that arbitrage is most limited when mispricings are most severe.

When arbitrage is risky there is no reason to assume that irrational investors will exit from the market. When noise traders and arbitrageurs are both bearing risk, the expected returns of each depends upon the quantity of risk they bear and on the compensation offered by the market for assuming such risk. It may be the case that, on average, the returns earned by arbitrageurs exceed those earned by uninformed investors. This does not imply that it is more likely that the former will get rich and the latter become poor in the long-run. Misjudgements of noise traders may lead them to take on more risk and be on average rewarded with higher average returns. This makes the proposition that irrationality in financial markets is irrelevant somewhat questionable.

Transactions costs are an impediment to arbitrage as they reduce the attraction of exploiting mispricings. There may also be short-sales impediments such as fees and legal constraints. Furthermore arbitrageurs face search costs before they begin to incur transactions costs. The outcome is that arbitrage in practice is both costly and risky. Under certain conditions costs and risks will limit arbitrage which, in turn, leads to persistent deviations of price from fundamental value.

Any mispricing which is persistent provides evidence of limited arbitrage. If arbitrage were not limited the mispricing would be removed. However a considerable obstacle in identifying a mispricing is the joint hypothesis problem. There are, however, some frequently cited examples of mispricing. Froot and Dabora (1999) provide a review of cases of twin securities. One prominent example is the relative mispricing of Royal Dutch and Shell equity which was sustained for several years despite shareholders of each being entitled to a constant proportion of the group's overall cash flows. This provides strong evidence of inefficiency and limited arbitrage as the shares are close substitutes for each other hence minimising fundamental risk. Also establishing short positions in either share should have been fairly straightforward ruling out any significant implementation costs. Thus the cause of the misalignment must have been investor sentiment. Barberis and Thaler (2002) point to the example that an arbitrageur buying a 10% undervalued Royal Dutch share in 1983 would have endured the mispricing increasing in severity over the following six months. It is plausible that in this case arbitrageurs were risk averse with short horizons, the risk was systematic and arbitrage required specialised research and skills. As further evidence the shares did not trade at their correct values until 2001.

Companies that are either included or removed from an index have been observed to change in value without any associated change in fundamentals. Harris and Gurel (1986) and Shleifer (1986) investigate stocks that are added to the S&P 500 and note that a stock jumps in price by an average of 3.5% despite no change in fundamentals. Inclusion in the S&P 500 does not imply any information about a firm's cash flows or level of risk. Inclusion should not be accompanied by significant share price reactions in response to new demand because the initial holders of included stocks should be willing to sell and to purchase substitute securities. However, Wurgler & Zhuravskaya (2002) find evidence to suggest that there are significant, sustained share price increases on news of inclusion in an index. Barberis, Shleifer and Wurgler (2005) investigate comovement in asset returns. They state that inclusion in an index should not affect the correlation of a stock's return with returns of other stocks. Barberis *et* al employ a bivariate regression to separate the sentiment and fundamentals theories of comovement. They find that, after inclusion in the S&P500 index, a stock's beta with the index increases which provides support for the sentiment theory of comovement.

The evidence on index inclusions casts doubt on a basic implication of EMH: the non-reaction of prices to non-information. Persistent reaction of prices to non-information provides support to the notion that arbitrage is limited. The arbitrageur faces considerable risk in attempting to exploit any mispricings because the strategy involves shorting the included security and simultaneously buying a close substitute. The key limitation is that individual stocks rarely have good substitutes. There is also considerable noise trader risk because the price trend may actually continue in the short run.

Equity carve-outs are a further example of limited arbitrage in cases where the stocks of the subsidiary become overpriced relative to those of the parent, as in the frequently cited example of the carve-out of Palm by 3Com in 2000. The market value of Palm following the IPO implied that the non-Palm business of 3Com had a significant negative value. This severe mispricing persisted for several weeks despite presenting a costless arbitrage opportunity with no fundamental or noise trader risk. According to Lamont and Thaler (2003) arbitrage was limited by implementation costs. Very few Palm shares were available to short and those that were had prohibitively high borrowing costs. The demand for shorting was so high that it could not be met and the mispricing persisted. In this case there were restrictions on short selling but these were market-determined rather than regulatory.

The debate continues amongst economists as to whether limited arbitrage affects the efficiency of markets. Proponents of EMH argue that only isolated cases exist whereas supporters of behavioural finance argue that limited arbitrage is much more widespread.

1.5 The Noise Trader Challenge to EMH

Excess volatility in financial markets is often attributed to the actions of noise traders. Hence it is important to provide a clear definition of noise. Noise relates to the random fluctuations in prices and trading volumes observed on financial markets that may be wrongly perceived as information. These random fluctuations can cause confusion about market direction and trends despite noise in reality being random and meaningless. Hence traders who make buying and selling decisions on the basis of this are regarded as uninformed or ‘noise’ traders.

Black (1986) formalised the distinction between informed and uninformed traders and characterised the former as trading on the basis of information and the latter as trading on the basis of 'noise'. Black argued that agents who trade on the basis of information are correct in expecting to make profits. In contrast, agents who expect to make profits, but trade on the basis of noise, as if it were information, are incorrect. This may be interpreted as noise traders’ beliefs that they are privy to special information gleaned from signals provided by acknowledged ‘experts’. Nevertheless, Black emphasises that noise trading is an essential requirement for the liquidity of markets. A further observation is that a large number of factors cause stock prices to stray from theoretical values. Black recognises the importance of the presence of noise in that, although it makes financial markets imperfect, it makes them possible. Black argues that in the absence of noise trading there would be very little trading in individual assets. Agents would merely trade in mutual funds, portfolios, index futures or index options to change broad market exposure. The key insight is that if an informed trader wanted to trade on information there would be no counterparty to the trade if all traders were fully informed. With no trading of individual securities there will be no trading in futures, options or other derivatives as there will be no way of correctly pricing them. It is the uninformed traders who provide liquidity to financial markets and provide an incentive for informed traders to trade. However, noise trading adds a disturbance component to the information component in stock prices.

Because value is not observable, it is possible for events that have no information content to affect price. The price of a stock will be a noisy estimate of its value. Noise creates the opportunity to trade profitably, but at the same time makes it difficult to trade profitably. People trade on noise firstly because they like to trade and secondly because they think they are trading on the basis of information rather than noise. This is not consistent with only taking actions in order to maximise the expected utility of wealth or with always making the best use of available information.

It is rather difficult to accept that people generally, and specifically investors, are always fully rational in their decision-making. However, as pointed out in section 1.2.1, proponents of EMH argue that irrational traders will be met in the market by rational traders whose trades will eliminate the irrational component in prices. When investors decide to buy shares it is likely that this decision will be influenced by at least some irrelevant information. It follows that investors will not always pursue passive investment strategies that would be the norm for uninformed traders under EMH.

Irrationality of individuals is highlighted by what is known as non-Bayesian expectation formation. This means that individuals systematically violate Bayes rule and other principles of probability theory when predicting outcomes under conditions of uncertainty. For instance, an investor might interpret a relatively short history of rapid growth in a firm’s earnings as representative and consequently extrapolate this too far into the future. The rapid earnings could merely be a chance event rather than conforming to the investor’s model. Such heuristics are useful in many situations but they may lead investors seriously astray. By overpricing the firm, future returns are lowered if past growth rates are not maintained and prices adjust to more realistic valuations. Hence investor expectations are not solely based on fundamental information.

1.6 Empirical challenges to EMH

1.6.1 Excess Volatility

An early key empirical challenge to EMH is presented by Shiller (1981). Shiller employs data from the S&P500 and Dow Jones Industrial Average to demonstrate that equity prices are considerably more volatile than can be justified by a simple model where prices are equal to the PV of expected future dividends. Excess volatility may be interpreted as prices changing for no reason or because of animal spirits or mass psychology.

Shiller examines whether the model of an efficient aggregate stock market is consistent with statistical evidence. Of particular concern is whether stocks are more volatile than can be justified if markets are truly efficient. A number of anomalies have been identified that are mostly considered small, isolated departures from market efficiency. For example the weekend effect and January effect are calendar effects which expose the possibility of earning consistent abnormal returns from basic trading strategies. Similarly the size, book to market ratio and earnings to price ratio effects are typical of pricing anomalies. However, if most of the volatility in the aggregate stock market cannot be rationalised then this presents a serious challenge to EMH.

Under EMH a share price is equal to the mathematical expectation, conditional on all available information, of the present value of all future dividends accruing to the share *(P_t*).* P_t* is not known *ex ante* so share price must be re-defined as the optimal forecast of P_t*. It follows that $P_t = E_t P_t$* which implies that any unexpected movements in stock price must be as a result of new information about fundamental value.

Testing for excessive volatility suffers from a joint hypothesis problem hence a model based on rational behaviour is required to provide a benchmark. Shiller selects a dividend valuation model which is consistent with stock prices being determined by fundamentals.

$$P_0 = \sum_{t=1}^{\infty} \frac{D_t}{(1+k)^t} \quad (1.1)$$

Shiller proposes that violations of what he termed variance bounds will indicate that stock prices are inconsistent with key economic variables; dividends and the discount rate.

$$P_t = V_t = \frac{E_t D_{t+1}}{(1+k)^t} + \frac{E_t P_{t+n}}{(1+k)^n} \quad (1.2)$$

Where:

E_tD_{t+I} = expected value, at time t, of dividends at time t+i

V_t = fundamental value

k = the required rate of return

E_tP_{t+n} = expected price, at time t, of the price at time t+n

The model assumes homogeneity of investor expectations of future dividends and a constant and known required rate of return.

Shiller's test of EMH is performed by computing V_t and comparing this with the realised stock price. The observed terminal price and dividend data is used with the assumed constant discount rate to produce a perfect forecast stock price.

P_t* = perfect forecast stock price (1.3)

The analysis is then repeatedly rolled forward one year at a time to create a series for P_t*:

$$P_t^* = \sum_{t=1}^{n-1} \frac{D_{t+i}}{(1+k)^t} + \frac{P_{t+n}}{(1+k)^n} \quad (1.4)$$

The actual price and the perfect foresight price will differ by the sum of the forecast errors of dividends weighted by the discount factor.

$$\omega_{t+1} = (D_{t+i} - E_tD_{t+i}) \quad (1.5)$$

In the absence of systematic forecast errors by investors the expectation would be that they would be close to zero on average over a long sample period. The weighted sum of the errors should be relatively small and broad movements in P_t* will be correlated with those in P_t.

Shiller graphed the two series and found little correlation with considerably more variation in P than in P*. The relationship between the variances of the two series was examined as in equation (1.6).

$$Var(x) = \sum_{t=1}^{n} \frac{(x - \bar{x})^2}{n-1} \tag{1.6}$$

Where *x* is either P_t* or P_t.

The series of forecast errors, η_t, can be observed in hindsight.

$$\eta_t = P_t^* - P_t \; or \; P_t^* = P_t + \eta_t \tag{1.7}$$

η_t is a weighted average of the forecast errors for dividends. If investors are rational then η_t will be independent of all information at time t when they make their forecasts and therefore be independent of P_t. The variance equation (1.8) is produced on the basis of equation (1.7).

$$Var(P_t^*) = Var(P_t) + Var(\eta_t) + 2Cov(P_t, \eta_t) \tag{1.8}$$

The presence of informational efficiency in the market will be consistent with a zero covariance term.

$$Var(P_t^*) = Var(P_t) + Var(\eta_t) \tag{1.9}$$

$$Var(\eta_t) > 0$$

$$Var(P_t^*) > Var(P_t) \tag{1.10}$$

Or,

$$VR = \frac{Var(P_t^*)}{Var(P_t)} > 1$$

Or,

$$SDR = \frac{\sigma(P_t^*)}{\sigma(P_t)} > 1 \quad (1.11)$$

VR and SDR are the variance and standard deviation ratios respectively.

Shiller argues that if rational information processing occurs and the market sets prices according to a dividend valuation model with a constant discount rate then the variance inequality should hold and VR and SDR should be greater than 1. The results of the variance bounds tests indicate that that inequality (1.11) is significantly violated. The actual price variance is approximately 5.6 times that of the variance of the perfect forecast stock price. The actual stock price is considerably more volatile than can be rationalised according to fundamentals. Shiller also examines the variability in real interest rates that would be necessary to equate Var(P_t*) with Var(P_t). He finds that the standard deviation of real returns needs to be greater than 4% per annum. This finding suggests that the results should not be significantly affected by relaxing the assumption of a constant required rate of return as the actual historical variability in real interest rates is much smaller.

Similar tests are performed by LeRoy and Porter (1981), using data from the S&P Composite Index and 3 major US corporations, whose findings support those of Shiller.

Marsh and Merton (1986) criticise Shiller's work arguing that dividends are non-stationary. The finding of non-stationarity is problematic for variance bounds tests as it implies that the population variances are functions of time and the sample variances are not a correct measure of the population variances. So the stochastic trends need to be removed from the data to meaningfully apply variance bounds tests. However Campbell and Shiller (1988) and Campbell (1991) develop models which allow for non-stationary dividends. When variance bounds tests are run, in each case, excess volatility remains.

A further argument is that, although the aggregate market may be wildly inefficient, individual stock prices may correspond, to an extent, to efficient markets theory. This is because there is predictable variation in the future paths of individual dividends whereas in the aggregate there are not. This means that movements among individual stocks appear much more reasonable than do movements in the market as a whole. Jung and Shiller (2002) find evidence to support this assertion.

The key implication from Shiller is that there is excess volatility in the aggregate stock market relative to the present value of expected cash flows implied under efficient markets. The search goes on for a way to rationalise this volatility however it does appear that aggregate markets contain a substantial amount of noise. Hence Shiller's work can be viewed as an important early contribution to the Behavioural Finance paradigm. However Shiller's work has limitations in that the variance bounds tests assume stationary dividends and a constant rate of interest. Furthermore Shiller only rejects a joint hypothesis of excess volatility and the validity of the dividend valuation model.

1.6.2 Anomalies in Returns

Challenging the strong-form EMH, small stocks have historically earned higher returns than large stocks. This superior return has been concentrated in January of each year yet there is no evidence that small stocks have a corresponding higher level of risk in January. Since both firm size and the coming of the month of January is information known to the market, this evidence points to excess returns based on stale information which contradicts semi-strong form EMH. However, both the small firm effect and the January effect appear to have weakened considerably in recent years. The market value of a company's equity relative to the book value of its assets gives a ratio that provides a rough measure of the cheapness of a stock. Companies with high market to book ratios are categorised as expensive 'growth' companies and those with low market to book ratios are the cheapest 'value' companies. Market to book ratios that are particularly high may reflect excessive market optimism about the future profitability of companies. This optimism can be a result of overreaction to past good news. De Bondt & Thaler (1987), Fama & French (1992), and Lakonishok, Shleifer and Vishny (1994) find that, historically, portfolios formed of companies with high market to book ratios have earned considerably lower returns than those with low market to book ratios. Also, it is apparent that portfolios of high market to book companies have higher market risk, and perform particularly badly in extreme market downturns and recessions. This challenges EMH as it seems that stale information can predict returns. Conversely Fama & French (1993, 1996) interpret a firm's size and market to book ratios as measures of the fundamental riskiness of a stock. Stocks of smaller firms or stocks of firms with low market to book ratios should produce higher average returns as they are fundamentally riskier according to their higher exposure to size and market to book factors. The converse is true for large stocks with high market to book ratios. Shleifer (2000) casts doubt on these economic interpretations and argues that it is uncertain how such critical indicators of fundamental risk, more important than market risk, have emerged when previously unnoticed. Fama and French (1996) speculate that low size and market to book ratios may be a proxy for distress risk but provide no direct evidence. Shleifer counters that if this were the case the size effect would not have disappeared and there is also no reason why it would be concentrated in January.

If stock prices react to non-information this would also pose a significant challenge to EMH. One of the largest one day percentage price falls in history was the 1987 crash, which happened without any apparent news. Many sharp moves in stock prices seem to occur without being accompanied by any significant news. This observation is consistent with excess volatility in stock prices. Roll (1988) finds that movements in prices of individual stocks are largely unaccounted for by public news or by movements in potential substitutes. Security prices appear to move in response to shocks other than news.

Many findings of inefficiency have been challenged on grounds such as data snooping, trading costs, sample selection bias and improper risk adjustment. However, recent evidence is much less favourable to EMH then that of the 1960s and 1970s. Summers (1986) argues that the failure to find contradictory evidence until recently is because many tests of market efficiency have low power in discriminating against plausible forms of inefficiency. It is often difficult to tell empirically whether some time series, such as the value of a stock index, follows a random walk or alternatively a mean-reverting process that might come from a persistent whim.

The cumulative impact of theory, evidence and practice has been to undermine the dominance of the EMH and to motivate considerable research into inefficient markets under the banner of behavioural finance.

1.7 Overreaction and Underreaction

A significant body of empirical evidence has been presented in favour of short-horizon underreaction and long-horizon overreaction in security markets. More recently some evidence has been presented which suggests similar phenomena exist in the options market. To date the vast majority of this evidence has been focused on the United States although research has been published that finds similar patterns in markets of other countries. The objective of this section is to review this body of evidence which will underpin consideration of the reconciliation of overreaction and underreaction proposed by Barberis, Shleifer and Vishny (1998) in the context of options markets in Chapter 2.

It is important to contextualise the significant challenge posed to EMH by the finding of underreaction and overreaction. When new information regarding a particular company is revealed investors are often anchored to their prior beliefs regarding the company's stock and hence are conservative in their trading patterns. Essentially, following a good piece of news, for example a positive earnings announcement, the price of a stock will rise but of an insufficient magnitude relative to the piece of news. There follows a period of gradual adjustment as the positive news is finally embedded into prices hence the price continues to trend upward following the initial adjustment. Bad news has a similar effect in that, after the initial negative reaction, prices continue to trend downwards.

Underreaction evidence identified in empirical research is generally over short horizons. More specifically, it is apparent that security prices underreact to news over horizons of up to 1 year. What this means in a market efficiency context is that, for example, good news is impounded too slowly into prices and hence has power in predicting future positive returns. Clearly this evidence challenges the weak-form version of EMH, which posits that, because share price should immediately adjust to reflect all available relevant information, there should not be any consistent abnormal returns to be made from analysing stock price history.

Conversely, over long horizons, empirical research in finance has also identified overreaction in security prices. In essence, following a sustained period of good or bad news regarding a particular company, investors interpret this as representative of the future behaviour of the company's stock price. That is, they extrapolate this trend into the future and in doing so overreact to pieces of information of the same sign. Once this error is recognised there follows a period of adjustment that appears as return reversals. In particular, over horizons of 3-5 years, where news is either consistently good or consistently bad, security prices tend to overreact. What this means is that, for example, a security associated with a long run of good news will tend to become overpriced before reverting to a mean value. This again is a challenge to the weak-form of EMH.

Moreover, the finding of underreaction and overreaction suggests that consistent superior returns may be available to sophisticated investors without any associated increase in risk. If markets do overreact, contrarian strategies, that is buying past losers and selling past winners, should yield abnormal returns. Similarly, if markets underreact in the short-run, then short-run momentum strategies, that is buying winners and selling losers, should yield abnormal returns.

1.7.1 Overreaction

A powerful challenge to the efficient markets hypothesis was presented in the seminal overreaction hypothesis proposed by DeBondt and Thaler (1985). De Bondt and Thaler investigate stocks traded on the New York Stock Exchange between 1926 and 1982 and compare the performance of two groups of companies. These are categorised as winners (W) that had previously enjoyed positive returns and losers (L) that had previously suffered negative returns. Portfolios are formed comprising the best and the worst performing stocks over the previous three years and cumulative abnormal returns are computed. DeBondt and Thaler set out the conditions that:

$$E\left(\tilde{u}_{W_t}|F_{t-1}\right) < 0, E\left(\tilde{u}_{L_t}|F_{t-1}\right) > 0 \qquad (1.12)$$

Thus over the following five years they find extremely high returns for the losers and relatively poor returns from the winners. This difference is not explained by the greater riskiness of the losers, at least using standard risk adjustments such as the CAPM. The findings are explained as stock prices overreacting; the losers have become too cheap and bounce back, the winners have become too expensive and earn lower subsequent returns. This apparent illustration of overreaction presented by DeBondt and Thaler is supported by the findings of a number of subsequent studies but rejected by others. Merton (1985) questions the finding of asymmetric overreaction. He argues that it is unsatisfactory that there is no clear theoretical explanation why overreaction results in losers winning almost three times what winners lose. Furthermore, Merton highlights the seasonality of the results in that most of the excess returns occur in January, implying that the overreaction hypothesis is mostly a January effect. Merton also argues that the reported statistical significance is likely to overstate the strength of the results.

DeBondt and Thaler (1987) present further evidence of overreaction when incorporating a time-varying risk coefficient (CAPM betas). They demonstrate that the excess performance for badly performing equities in the test period is negatively correlated with both long- and short-run formation period performance; i.e. overreaction effects persist. DeBondt and Thaler make adjustments for firm size and conclude that overreaction is not primarily a size effect. However they do find that a large proportion of the contrarian profits are earned in successive Januarys.

Evidence of overreaction is also presented by Jegadeesh (1990) and Lehman (1990). Both studies discover overreaction and the profitability of contrarian strategies over one and six month horizons respectively.

Although there is substantial evidence of stock market overreaction over both short and long horizons there is a lack of consensus about why it occurs. In particular, explanations of market overreaction have been proposed which can be reconciled with the EMH. These may be summarised as thin trading (Lo and MacKinley, 1988), differential risk (Chan, 1988), data biases (Lakonishok, Shleifer and Vishny, 1994) and bid-ask biases (Conrad, Gultekin and Kaul, 1997).

Lo and Mackinlay (1988) offer an explanation for the observed serial correlation in stock returns. They argue that this may merely be due to infrequent trading resulting in stale prices. This work is followed up by Lo and MacKinlay (1990) who find that much of the perceived profit from contrarian investment strategies can be attributed to cross effects among stocks. Furthermore these cross effects demonstrate a lead-lag effect in stock returns of size-sorted portfolios. That is, the returns from larger stocks generally lead those from smaller stocks. This implies that stock market overreaction is not the only explanation of contrarian profits, as these may be available even if no stock overreacts to information.

Chan (1988) criticises the work of DeBondt and Thaler (1985) for failing to adjust for the riskiness involved in implementing long-term contrarian strategies. Chan argues that the reversal in returns reflects changes in equilibrium required returns which are not controlled for in DeBondt and Thaler (1985). Chan employs the Capital Asset Pricing Model (CAPM) to demonstrate that very small returns earned by contrarian strategies are most likely economically insignificant. He argues that the estimation of abnormal returns is sensitive to the procedure employed. The betas of previous loser stocks will increase after the formation period whilst the betas of previous winners will decrease. Thus losers are riskier and have a higher expected return in the subsequent period, the opposite being true for the winners. In the sample of DeBondt and Thaler (1985) the beta of the arbitrage portfolio increases by 0.604 from the formation period to the testing period. It follows that betas from the past cannot be employed. Furthermore, it is incorrect to analyse the relationship between average return and average beta because both the betas and the expected market risk premium may react to some common variables and hence show correlation. Ball and Kothari (1989) support the findings of Chan (1988) in that the betas of extreme losers exceed those of extreme winners by 0.76 in the period following portfolio formation.

Zarowin (1990) examines whether market overreaction may be due to either size or seasonality effects and produces results which indicate a reduction in excess returns from losers when firm size is controlled for. Without adjustment for firm size, losers significantly outperform winners. Neither the January effect nor differences in risk can account for these results. When winners and losers of comparable size are analysed, significant differences are only apparent in January. Zarowin proposes that since losers tend to be small and small firms outperform large firms, abnormal returns occur as a result of size discrepancies between winners and losers. Thus overreaction may simply be another manifestation of the size effect. Pettengill and Jordan (1990) find that the smaller the firms are then the larger are the contrarian profits. They also discover that overreaction is strongest in January. Clare and Thomas (1995) test the overreaction hypothesis using UK data from 1955 to 1990 and also confirm that a size effect is present. They find evidence of overreaction but note that contrarian profits are unlikely to be economically significant. The general implication of these studies is that market overreaction is at least partly a product of the size and January effects.

Poterba and Summers (1988) find long-term serial correlation among stocks listed on the London Stock Exchange. Dissanaike (1997) examines both extreme winners and losers and intermediate performers and finds evidence that generally supports the overreaction hypothesis. The analysis is restricted to large, well-established companies. The rationale for this sample is to minimise any biases caused by bid-ask effects and thin trading. In addition, the study seeks to establish whether or not overreaction can be explained by time-varying risk. No evidence is found to suggest that this is the case.

Conrad and Kaul (1993) suggest that the overreaction hypothesis might be explained by factors such as bid-ask biases and infrequent trading. They show that long-term contrarian profits are upwardly biased since they are obtained by cumulating single-period returns over long periods. This cumulates both true returns and the upward bias in single-period returns caused by measurement errors such as the bid-ask effect. Using a buy and hold performance measure and excluding January, they show that there is no evidence of contrarian profits. Moreover, they argue that the actual return on an arbitrage portfolio of winners and losers is only explained by the January effect. However, there is no relationship between the January effect and the prior performance of stocks. Their findings lead to a conclusion that it is a combination of the January effect and biased performance measures that lead to overreaction and contrarian profits. An important implication of Conrad and Kaul's work is that cumulative abnormal returns (CAR's) should not be used to reflect the effect of new events on stock prices as this may introduce bias particularly with high frequency data.

Conrad, Gultekin and Kaul (1997) argue that negative serial covariance caused by bid-ask errors in transactions prices are key to explaining profits from short-term contrarian strategies rather than overreaction. This conclusion is reached when returns used are computed using bid prices that do not include bid-ask errors.

Loughran and Ritter (1996) disagree with Conrad and Kaul. They argue that it is the use of a pooled cross section time series regression, where prices predict market returns, that leads to most of the different results in Conrad and Kaul (1993). It is argued that Conrad and Kaul confound cross section patterns with time series patterns. Additionally, they misstate their t-statistics by ignoring the contemporaneous correlations of residuals of stocks from the same year and introduce a survivorship bias. Loughran and Ritter find that it is neither CARs nor buy and hold performance measures that lead to the overreaction results of DeBondt and Thaler (1985). Also, when portfolio formation is based upon CARs, the bid-ask bias leads to some low-priced stocks being classified as winners despite low ranking-period buy and hold returns, thereby lowering the power of tests. When portfolio formation is based upon buy and hold returns, losers outperform winners by more than CARs. When price is employed for portfolio formation, subsequent return differences are even larger. Loughran and Ritter (1996) provide evidence that the losers whose prices are below five dollars have the highest subsequent buy and hold returns, however all of the extra returns come from January. Following a bull market few losers are in this low-price category but following a bear market numerous losers are. This makes it difficult to separate aggregate market mean reversion from price effects.

Jegadeesh & Titman (1993) demonstrate that movements in individual stock prices over a period of six to twelve months tend to predict future movements in the same direction. This shows that relatively short-term trends continue thus challenging the weak form EMH.

Jegadeesh and Titman (1995) investigate price reaction to both common and firm-specific factors. They discover that stock prices display delayed reaction to common factors but overreact to information that is specific to the firm. They also note that although both overreaction and delayed reaction could give rise to profitability of contrarian strategies, delayed reaction cannot be exploited by contrarian strategies.

Further, it is shown that the most important source of observed profits from contrarian strategies is the reversal of the firm-specific component of returns. This is generally considered to be a correction of prior overreaction. Additionally, Jegadeesh and Titman (1995) propose that return reversals may also be induced by price pressure from liquidity motivated trades. Under this explanation, the return reversals and contrarian profits seem to decline over time as the liquidity of the market increases.

Lakonishok, Shleifer and Vishny (1994) suggest that biased data source and selection offer an alternative explanation of overreaction.

Evidence on overreaction is available from a variety of markets. For example, Da Costa and Newton (1994) employ data from the Brazilian stock market from 1970 to 1989. They find that these stocks demonstrate higher price reversals than are observed on the New York and American Stock Exchanges. They also find evidence of asymmetric overreaction, although differential risk is unable to explain these results. Bowman and Iverson (1998) present similar results when investigating weekly observations on New Zealand stock market data. Bremer and Hiraki (1999) study data from the Tokyo Stock Exchange and demonstrate overreaction in the period 1981-1998. Grinblatt and Keloharju (2000) find evidence to suggest that contrarian investment strategies may yield excess profits in the Finnish market. Chang, Mcleavey and Rhee (1995) find that short-term contrarian strategies would yield abnormal profits in the Japanese stock market. Their findings are similar to those of Hameed and Ting (2000) who investigate the Malaysian stock market. Kang, Liu and Ni (2002) investigate Chinese 'A' shares from 1993 to 2000. They find statistically significant excess returns to short-horizon contrarian investment strategies hence providing support for the overreaction hypothesis. Overreaction is attributed to a size-related lead-lag structure due to investors having less information on small firms than on large firms. However, Kang et al's study is limited by the relatively short history of available data. Thus long-term horizon analysis is not possible. The Canadian stock market is studied by Assoe and Sy (2003). They discover that short-term contrarian strategies would have been profitable between 1964 and 1998. However these profits would not have been economically significant in the presence of transactions costs. The results would also appear to be determined by the small firm and January effects.

A significant body of research, using various samples from a number of countries, points to stock market overreaction. However it is important to note the differences between the data and methodologies employed. There is disagreement regarding the choice of frequency. For example, Ball and Kothari (1989) indicate that when annual rather than monthly returns are analysed the evidence of market overreaction appears to be weaker. Conrad and Kaul (1993) argue that more frequent returns, such as daily, can result in cumulative abnormal returns being upwardly or downwardly biased due to bid-ask effects.

There is also variation in the duration of formation and testing periods. Jegadeesh (1990) and Lehman (1990) examine the overreaction hypothesis in short-term horizons (one and six months respectively). In contrast, De Bondt and Thaler (1985) study long-term horizons (three to five years).

A further variation is the basis for portfolio formation. The majority of studies form winner and loser portfolios based on cumulative abnormal returns. The study of Conrad and Kaul (1993) differs in that they employ a buy and hold performance measure. Furthermore, Conrad, Gultekin and Kaul (1997) employ returns computed from bid prices that do not contain bid-ask errors.

There are also differences in the ways in which abnormal returns are defined. Generally a variety models, in particular CAPM, the market model and the Fama and French three-factor model, have been used to generate abnormal returns. Antoniou, Galariotis and Spyrou (2005) investigate the Athens Stock Exchange and find that the detection of contrarian profits is very sensitive to the definition of abnormal returns. For example, when market-adjusted returns are used, a variety of strategies fail to produce abnormal returns. However, when risk-adjusted returns are used there is evidence of the availability of contrarian profits from long-term strategies. Most of these profits can however be eliminated when a Kalman Filter algorithm is used to compute the risk-adjusted returns and time-variation in systematic risk is allowed for. Hence, it is suggested that returns are merely appropriate for the level of systematic risk and the Athens Stock Exchange may be efficient. Although this procedure is applied to an emerging European market which would be expected to exhibit a high level of volatility, apparently no attempt has been made to compare this with a more developed market.

There are also inconsistencies in the way winners and losers are defined. De Bondt and Thaler (1985) define the best and worst 35 performing stocks over their monitoring period as the winners and losers respectively. However, Zarowin (1990) considers the top and bottom quintiles of the samples as the winners and losers. Clare and Thomas (1995) use similar definitions to Zarowin. They propose that adopting this method will allow the most rigorous test of the portfolio. Antioniou, Galariotis and Spyrou (2004) select the five top performing stocks and the bottom five performing stocks in their study, which takes consideration of transactions costs.

Evidence of overreaction is presented in the literature. However, many of the findings are sensitive to factors such as the choice of sample period, market index, models for risk adjustment, definition of winners and losers and duration of formation and testing periods. Whilst critics of the overreaction hypothesis argue that contrarian profits disappear once appropriate adjustments are made for risk.

1.7.2 Underreaction

Several studies uncover significant evidence of underreaction which in turn suggests that momentum strategies may be profitable. If post-earnings announcement price drifts can be identified then there will be opportunities to earn consistent superior returns.

Ball (1978) observed that stock prices underreact to public earnings announcements leading to the availability of consistent abnormal returns during the post-announcement period. This is result is particularly apparent when announced earnings differ significantly from expected earnings. Ball hypothesises that earnings act as a proxy for omitted variables from a two-parameter asset pricing model.

Bernard and Thomas (1990) investigate a sample of 2,626 firms over the period 1974 to 1986 and find evidence to indicate that earnings changes exhibit a slight trend at one, two and three quarter horizons and a slight reversal after a year. Bernard and Thomas interpret this finding as evidence that investors do not recognise positive autocorrelations in earnings changes, rather they believe that earnings follow a random walk. This belief causes them to underreact to earnings announcements. The key suggestion is that underreaction occurs because investors typically believe that earnings are more stationary than they are in reality. This idea has firm foundations in psychology.

A study of the Toronto Stock Exchange by Kryzanowski and Zhang (1992) identified significant underreaction over one- and two-year horizons along with insignificant reversal behaviour over longer horizons of up to ten years. Jegadeesh and Titman (1993) consider transactions costs in their study of US markets from 1965 to 1989 and find evidence of significant market underreaction and momentum profits. This finding is supported by Cutler, Poterba and Summers (1991) who investigate returns in stock, bond and foreign exchange indexes for the period 1960-1988 and find evidence of underreaction. Fama and French (1996) argue that their three-factor model can provide an interpretation of most of the return predictability, however it cannot provide an explanation for underreaction profits.

Bernard (1992) summarises studies relating to the cross-section of expected returns in the United States. The studies surveyed sort stocks into groups based on how much of a surprise is contained in their earnings announcement. The simple construct employed to quantify an earnings surprise is standardised unexpected earnings (SUE). This is defined as the difference between a company’s earnings in a given quarter and its earnings during the same quarter in the previous year. This is scaled by the standard deviation of the company’s earnings. An alternative measure of an earnings surprise is the stock price reaction to an earnings announcement.

Jegadeesh and Titman (1993) investigate the potential to earn abnormal returns by implementing relative strength trading strategies. That is, buying past winners and selling past losers. They find evidence that returns on NYSE and AMEX stocks between 1965 and 1989 exhibit positive autocorrelation. Jegadeesh and Titman offer a number of key findings. Firstly, profits from the strategies do not arise from their systematic risk. Second, the profits do not result from any lead-lag effect that may be present as a result of delayed stock price reactions to information about a common factor. Third, the findings are consistent with delayed price reaction to firm-specific information. They assert that this momentum is an indication that investors underreact to information.

Chan, Jegadeesh and Lakonishok (1997) find evidence to support the hypothesis that investors underreact to news and incorporate news into prices slowly. They integrate the evidence on earnings drift with that on momentum. Chan *et al* employ three methods to measure earnings surprises. These are SUE, stock price reaction to the earnings announcement and revisions in analyst's forecasts of earnings. All of these measures, as well as past returns, have predictive power for subsequent stock returns at horizons of six months and one year. Stocks with a positive earnings surprise, as well as stocks with high past returns, are found to subsequently outperform stocks with a negative earnings surprise and poor returns. Chan et al conclude that their evidence indicates underreaction to news and the slow incorporation of information into prices.

Ikenberry, Lakonishok and Vermaelen (1995) investigate short-term and long-term company performance following the announcement of open market share repurchases by US companies between January 1980 and December 1990. They note that undervaluation seems to be a key motivating factor for managers to initiate share repurchases thus providing a signal to investors. Nevertheless, Ikenberry *et al* find that significant abnormal returns are available, particularly for 'value' stocks, because market participants underreact to the signal provided by repurchase announcements. Michaely, Thaler and Womack (1995) find that markets underreact to cash dividend initiations followed by a post announcement drift.

Loughran and Ritter (1995) examine a large sample of US companies between 1970 and 1990 and find that the performance of stocks following initial public offerings and seasoned equity offerings is poor relative to stocks of companies that do not issue new equity. They argue that an issue of new equity is a signal of bad news, however investors underrect to this news hence there is subsequent underperformance. In fact Loughran and Ritter’s results imply that 44% more funds would need to be invested in issuers than in non-issuers to achieve equivalent final wealth over a five year holding period. Loughran and Ritter offer a partial explanation of this result as companies taking advantage of transitory windows where the company is perceived as overvalued.

Spiess and Affleck-Graves (1995, 1999) find similar evidence of underreaction to that of Loughran and Ritter when examining the post issue performance of equity following seasoned equity offerings and following the issue of debt securities. Spiess and Affleck-Graves (1995) investigate the seasoned equity offerings of US companies. The sample is restricted to only primary seasoned offerings and covers the period from 1975 to 1989. Post-issue performance is then analysed for up to five year horizons. The interpretation of the finding of underperformance is attributed to asymmetric information and managers’ ability and willingness to time the market. Hence long-run underperformance is a direct result of slow interpretation and adjustment to the market signal provided by the offering. Spiess and Affleck-Graves (1999) use the same sample period and discover that companies making new debt, including convertible debt, offerings suffer considerable long-run post-issue underperformance. The explanation is once more underreaction to the negative signal of a new issue of securities.

1.7.3 Reconciling Overreaction and Underreaction

The key behavioural explanations of underreaction and overreaction are provided by Barberis, Shleifer and Vishny (1998), Daniel, Hirshleifer and Subrahmanyam (1998) and Amir and Ganzach (1998). Of particular interest to this study is the model of Barberis, Shleifer and Vishny. A substantial body of evidence from stock markets has been reviewed in the preceding section which points to two key findings. Firstly, markets appear to underreact to short term changes. Second, the same markets tend to overreact to sustained changes. Barberis, Shleifer and Vishny present a model which seeks to reconcile these two observations and is based on psychological evidence. The key to this model is to explain how investors form beliefs that can consequently lead to both underreaction and overreaction. They posit that financial markets are populated by a representative investor who is prone to both conservatism and the representative heuristic. In the first instance the investor is strongly influenced by prior beliefs and hence tends to underreact to individual pieces of information. This is consistent with the definition provided by Edwards (1968). In the second instance, once a pattern has been (too readily) identified in the data the investor believes this to be representative and so overreacts to periods of mostly similar information. This second finding is consistent with Tversky and Kahneman (1974) on representativeness in experimental subjects. The model is based on limited arbitrage where investor sentiment is unpredictable and potential arbitrageurs face the risk that the deviations of prices from fundamental value can be sustained or even exacerbated by investor sentiment. The representative investor believes that firm earnings switch between mean-reversion and trending. When this switch will occur is in the investor’s mind. As earnings are observed the investor updates his beliefs. For example, earnings surprises of the opposite sign reinforce the belief of mean-reversion, whereas earnings surprises of the same sign increases the probability, in the investor’s mind, of a trending regime.

Daniel, Hirshleifer and Subrahmanyam (1998) employ the psychological concepts of overconfidence in the precision of investor information and biased self-attribution to produce a model of investor sentiment which also seeks to reconcile the evidence on overreaction and underreaction. Daniel *et al* define an overconfident investor as being prone to overestimate the precision of private information but not that of publicly available information signals. The private signal is overweighted leading to overreaction followed by more public information becoming available which ultimately leads to a price correction. In short, Daniel *et al* argue that stock prices overreact to private information and underreact to public information. This is illustrated by informed managers buying back their own company stock when they perceive it to be underpriced. The information signal then becomes public and acts as a predictor of future positive returns. Following a successful decision by an overconfident investor this overconfidence is reinforced by the self-attribution bias. This leads to momentum in equity prices which is eventually corrected as public information becomes fully available. Hence there is short-run momentum followed by long-run price reversals. In their theoretical model Daniel *et al* are unable to identify any class of investor that overconfident traders belong to.

Amir and Ganzach (1998) investigate over and underreaction in the context of the forecasts of security analysts. They demonstrate that analysts overreact when changing forecasts relative to the previous year but underreact when updating forecasts within the current year.

Hong and Stein (1998) examine the interactions between momentum traders and news watchers. They argue that this interaction leads to underreaction and overreaction because momentum traders trade on the basis of price patterns whilst ignoring information about fundamentals. Conversely news watchers trade on the basis of information on fundamentals but ignore price patterns.

Underreaction and overreaction present a significant to challenge to the efficient markets hypothesis. These phenomena will be investigated further in the context of options markets in Chapter 2.

Fama (1998) provides a detailed article criticising behavioural finance and supporting the efficient markets hypothesis. Fama's first objection is that overreaction and underreaction occur roughly as frequently as each other and effectively cancel each other out. Consistent with an efficient market they become random fluctuations. His second objection is to the methodologies employed to produce long-term return anomalies. Fama argues that using different models for normal expected returns reduces anomalies to chance events. He attacks behavioural finance as not testing specific alternatives to market efficiency so that the alternative hypothesis is vague. This means that no better model is being proposed that can itself be subjected to a rigorous testing procedure. The interpretation of results from tests of long-term return reversals also come in for criticism. Fama argues that long-term return continuation is almost as frequent. Fama goes through a range of studies, particularly in relation to corporate restructuring and provides similar criticism. The most powerful criticism is that of methodologies and the use of relatively small t-statistics as evidence of a result. T-statistics that Fama argues could easily become insignificant following an adjustment to methodology.

1.8 The Closed End Fund (CEF) Puzzle

A closed end fund (or investment trust) is a fund which typically holds other publicly traded securities and issues a fixed number of shares that are traded on the stock market. To liquidate a holding in a fund, investors must sell their shares to other investors rather than redeem them with the fund itself for the net asset value per share as they would with an open end fund.

The seminal behavioural article on the closed end fund puzzle is by Lee, Shleifer and Thaler (1991). Many of the points in this section are interpretations of issues in this article. The closed end fund puzzle is the empirical finding that shares in these funds typically sell at prices not equal to the per share market value of assets the fund holds; known as the net asset value (NAV). These shares occasionally trade at a premium but commonly trade at a discount. For example, Gemmill and Thomas (2002) note that, over a 30 year period, the average discount was 18 percent in the United Kingdom and 14 percent in the United States.

Lee, Shleifer and Thaler (1991) identify four important components of the puzzle which characterise the life cycle of a closed end fund:

1. When first initiated funds have a premium of almost 10% on average. This premium arises because of underwriting fees and start-up costs which reduce the NAV relative to stock price. It appears counter-intuitive that investors would be willing to pay a premium to invest in new funds when existing funds normally trade at a discount.
2. Within 4 months of start-up closed end funds are usually trading at a discount of over 10% and such discounts remain the norm. However, Berk and Stanton (2005) have demonstrated that, with larger samples, the speed with which discounts appear is much slower.
3. There are significant fluctuations in discounts although they appear to be mean-reverting. This observation raises the possibility of earning consistent abnormal returns from buying deeply discounted funds.
4. On the termination of a fund, through either liquidation or open ending, fund prices rise and discounts shrink when the announcement is made.

One question that is difficult to answer is why investors continue to subscribe to IPOs in closed end funds that subsequently trade at a discount when they could invest in open ended funds which always trade at their par value.

There have been several explanations offered for the closed end fund puzzle. These explanations vary from being unconvincing to very plausible.

The agency costs explanation rests on the argument that fund managers incur high running costs and don't perform as well as they should. This reduces the value of the fund relative to NAV. However fluctuations in discounts appear to be too wide to be justified by agency costs. Furthermore management fees are typically a fixed percentage of NAV and do not fluctuate as much as discounts. The agency costs explanation fails to address why investors are willing to pay a premium for a fund which is expected to eventually trade at a discount.

Illiquidity may explain the puzzle if funds have holdings of assets that are subject to trading restrictions. The market value of restricted stock is generally lower than that of its unrestricted counterpart. Calculating NAV may overvalue these stocks leading to a price which is below NAV. This explanation is problematic as only a small proportion of funds hold restricted stock. Many of the largest funds that trade at discounts hold only liquid publicly traded securities. Nevertheless Malkiel (1977) finds that there is a relationship between the quantity of restricted stock held and the size of the discount. Hence restricted stock holdings may explain a portion of the discount on certain selected funds but not for the substantial discounts of large, diversified funds. However Cherkes, Sagi and Stanton (2009) revive the liquidity argument by modelling the relationship between the fees paid by investors and the perceived benefit of funds' liquidity compared to that of the underlying assets.

Investors see closed end funds as a way to add illiquid underlying assets to their portfolios by taking liquid positions in closed end funds. By adopting this approach Cherkes *et al* conclude that the liquidity argument cannot be dismissed as a partial explanation for the close end fund puzzle. However they are unable to fully account for purchases of fund shares in IPOs when similarly priced seasoned funds offer superior performance.

CEFs often hold blocks of individual securities which may only be liquidated quickly at a price which is below the market price. Most transactions in equity markets involve a relatively small number of shares so it follows that the quoted market price is usually that of the marginal share. NAV is calculated using the price of the marginal share hence the proceeds from a block sale will be below the NAV. The block trading perspective seems dubious given that CEF prices actually rise on the announcement of fund liquidation or open ending.

Discounts may arise because NAV fails to reflect any capital gains tax that needs to be paid by the fund if the constituent assets are sold. This explanation is contradicted somewhat by the rising prices that are observed when termination of a fund is announced. Furthermore, CEF prices converge on NAVs from below rather than NAVs converging to fund share prices from above. The latter would clearly be expected if the measured NAVs were too high.

Key to the behavioural finance explanation is that investor sentiment about future returns from holding the fund will fluctuate. The notion of fluctuating investor sentiment permits development of a model which is consistent with empirical evidence and yields testable implications. It separates the fund, F from its underlying portfolio, S. Assuming noise traders' beliefs about the return on F relative to the return on S are subject to fluctuating sentiment, optimism about F leads to noise traders driving CEF prices relative to fundamental values. Similarly, the actions of pessimistic noise traders drives down the price of F relative to that of S. Importantly, any variations in noise trader sentiment will be unpredictable.

Holding a CEF exposes the investor to price risk from holding the fund's portfolio and to noise trader risk from fluctuating sentiment. Any investor holding a CEF risks the discount widening in the future if noise traders become relatively more pessimistic about CEFs.

Less-sophisticated individual investors are likely to hold and trade a relatively large proportion of CEF shares but a relatively small proportion of the assets contained in the funds' investment portfolios. Weiss (1989) observes that CEFs are owned and traded primarily by individual investors. The same group of investors also account for significant holdings of low market capitalisation shares. Assuming that small stocks and CEFs are subject to the same individual investor sentiment, fluctuations in the discounts on CEFs should be correlated with small stock returns. Co-movement is testable and, if found, would be inconsistent with market efficiency.

In a fully efficient market the mispricing of a CEF relative to its constituent portfolio should be eliminated by arbitrage. The purchase of an underpriced CEF and simultaneous short sale of its underlying portfolio will not be perfect arbitrage unless arbitrageurs have an infinite time horizon and are never forced to liquidate their positions. If arbitrageurs need to liquidate at some finite time then they face the risk that the discount will become wider after the arbitrage is initiated resulting in a loss. Arbitrageurs would never need to liquidate their positions if they received the full proceeds from the initial short sales, since the initial investment would have been negative and all future cash flows would be zero. However, as full use of the proceeds is normally restricted, they may need to liquidate positions in order to obtain funds. Here, bearing noise trader risk is unavoidable. Because arbitrage against noise traders is not riskless, arbitrageurs can take only limited positions and mispricing can persist.

Pontiff (1996) examined a cross-section of CEFs and found that higher levels of costs are generally associated with greater mispricing of CEFs relative to their portfolios.

A possible alternative to ‘buy and hold’ arbitrage is to take over a CEF and subsequently sell off its assets to realise the NAV. Grossman & Hart (1980) found that shareholders will demand the full NAV from bidders. Also managers resist bids wiping out potential profits. Consequently there is little profit from CEF takeovers after transactions costs so it is unsurprising that they are not common.

The behavioural approach of Lee, Shleifer and Thaler (1991) provides an appealing explanation of the four parts of the CEF puzzle. Because holding a CEF is riskier than holding its portfolio directly, and because this risk is systematic, the required rate of return on assets held as fund shares must, on average, be higher than that on the same assets purchased directly. So, the fund must sell at a discount to NAV to attract investors. The average underpricing of CEFs comes solely from the fact that holding the fund is riskier than holding its portfolio.

This theory implies that, during periods when noise traders are particularly optimistic about CEFs, entrepreneurs can profit by collating assets into CEFs and selling them to noise traders. Only noise traders, who are too optimistic about the true expected return on the fund’s shares, buy them initially when the expected return over the next few months is negative. So CEFs provide an opportunity for sophisticated entrepreneurs to benefit at the expense of a less sophisticated public.

Discounts on CEFs fluctuate with changes in investor sentiment about future returns. It is the fluctuations in the discounts that make holding the fund risky and therefore account for average underpricing.

Share prices rise on the announcement of open ending and discounts first fall and are then eliminated at the time open ending or liquidation occurs. Once it is known that a fund will be open ended or liquidated, noise trader risk will be eliminated along with the discount. When open ending or liquidation is announced any investor can buy the fund and sell short its portfolio knowing that upon open ending his arbitrage position can be profitably closed with certainty. The risk of having to sell when the discount is even wider no longer exists; that is the noise trader risk has gone. The investor sentiment theory predicts that any discounts which remain after the announcement of open ending or liquidation should become small or disappear eventually.

New funds are initiated when noise traders are optimistic about their returns. This should happen when investors also favour seasoned funds (as they are close substitutes for new funds). This implication may be tested by examining the behaviour of the discounts on seasoned funds when new funds are started.

For investor sentiment to affect CEF prices despite the workings of arbitrage, the risk created by changes in investor sentiment must be widespread. That which affects discounts on CEFs must affect other assets as well. Smaller cap stocks, as well as other stocks held and traded predominantly by individual investors, are likely to be influenced by the same sentiment as CEFs. This implies, contrary to the basic notion of efficient markets, that there will be a comovement in the prices of fundamentally unrelated securities solely because they are traded by similar investors and therefore influenced by similar sentiment. This would contradict the EMH view that security prices should not move in the absence of news.

These implications are not satisfactorily explored by other theories of CEF discounts. Lee, Shleifer & Thaler (1991) examine CEFs that were traded in the US over the period 1960-86. Lee *et al* find that the discounts on CEFs are positively correlated suggesting that they are driven by the same investor sentiment. However, they also find that the changes in, and levels of discounts are not strongly related to aggregate stock market returns indicating that the sentiment does not extend to the overall market. Furthermore, whenever discounts are low there are clusters of fund start-ups. A comovement effect is identified with discounts widening whenever the stocks of relatively small companies perform poorly and vice versa. The evidence of comovement is significantly weaker with stocks that have relatively large market capitalisation.

Individual investors are significant holders and traders of smaller stocks so changes in their sentiment should affect both CEFs and smaller stocks. Portfolios of stocks ranked by size are considered. For decile 10, the largest firms, stock prices do poorly when discounts narrow. For the other nine portfolios, stocks do well when discounts shrink. When individual investors become optimistic about CEFs and smaller stocks, these stocks do well and discounts narrow. When individual investors become pessimistic about CEFs and smaller stocks, smaller stocks do badly and discounts widen.

For the smallest stocks, which typically have the highest individual ownership, the comovement with CEFs is the greatest. For larger cap stocks, which have lower individual ownership, this comovement is weaker. The largest stocks seem to move in the opposite direction to the discounts.

Brauer and Chang (1990) find that the prices of CEFs exhibit a January effect even though the prices of the funds' portfolios do not. The CEF discounts are found to shrink in January. Ritter (1988) finds that 40% of the year-to-year variation in the turn-of-the-year effect is explained by the buying and selling activities of individual investors. These findings support the notion that CEF prices are affected by individual investor trading, some of which occurs at the end of the year, rather than purely by company fundamentals.

A further argument is that fluctuations in discounts do reflect the additional risk from holding a fund rather than its portfolio but this is fundamental rather than noise trader risk. It may be that small firms are affected by the same fundamental risk. This argument is not necessarily plausible as funds holding predominantly large stocks appear to co-move with smaller stocks.

Lee *et al.* (1991) look at the relationship between the value-weighted discount and the fundamental 'risk' factors identified by Chen, Roll and Ross (1986). If the discounts are highly correlated with measures of fundamental risk, then the investor sentiment interpretation may be suspect. Lee *et al* find that changes in discounts are not correlated with changes in 'fundamental' factors, except for a weak and not obviously interpretable correlation with changes in the expected inflation rate. Consistent with the investor sentiment interpretation, Malkiel (1977) found that discounts on CEFs narrow when there are more purchases of open end funds than redemptions. Malkiel’s interpretation of this finding is that similar changes in investor demand drive open fund purchases and closed end fund appreciation. Investors, whose sentiment changes, are also investors in open end funds and tend to be individual rather than institutional investors.

Analysis of the closed-end fund puzzle produces two broad implications. Firstly, there is clear evidence of comovement between fundamentally unrelated securities. Comovement occurs because of the influence of investor sentiment on fund prices under conditions of limited arbitrage. It is very difficult to reconcile this finding with the notion of market efficiency. Secondly, and most importantly, the finding of comovement demonstrates that behavioural finance can and does produce new empirical hypotheses of inefficient markets that can be examined with market data. This begins to answer the common criticism of behavioural finance that its predictions are difficult to test empirically.

Gemmill and Thomas (2002) use retail investor flows into particular sectors of UK funds as a proxy for noise trader sentiment in order to examine fluctuations in the closed end fund discount.[6] Although changes in discounts are found to be a function of time-varying noise trader demand, the key drivers of the level of closed end fund discounts are identified as the combination of arbitrage costs and managerial expenses. Gemmill and Thomas find that funds whose managers charge fees, but provide little or no value in return, will trade at a discount to net asset value. The discount depends upon the proportion of value paid to managers along with the proportion paid out to investors. Although this is a plausible explanation for discounts *per se*, it does not address why closed end funds trade at a discount whilst similar open end funds trade at net asset value.

Rather than focus exclusively on managers' fees, Berk and Stanton (2007) examine the managerial ability explanation of the frequently observed discount on closed end funds. Their starting point is the apparent lack of ability of fund managers to add value. Berk and Stanton posit that a trade-off exists between managerial ability and

[6] Investment flows of small investors into closed end funds are used as an indicator of investor sentiment.

fees which can account for fluctuations in discounts. Investors will be willing to pay a premium where managers have a high level of ability however these high-performing managers will also demand large fees. Therefore the size of discount (or premium) depends upon investors' expectations about managerial performance and the nature of managers' compensation contracts. The managerial approach is motivated by the findings of a number of authors who produce evidence that the stocks that closed end funds buy significantly outperform those that they sell.[7]

Berk and Stanton find that managerial ability combined with the manager's labour contract, particularly where bad managers become entrenched, provides a partial explanation for the closed end fund puzzle. The weakness of Berk and Stanton's model is that it fails to account for the predictability of fund returns, indicative of a lack of competition amongst investors. They also find that managerial turnover is a driver of discounts. In particular, funds with a recent change of manager exhibit above normal net asset value returns whilst those with a long-term incumbent exhibit below normal net asset value returns. This finding supports that of Wermers, Wu and Zechner (2005). Furthermore, Berk and Stanton's model predicts that discounts widen when good managers leave a fund voluntarily.

The models constructed by authors such as Berk and Stanton (2007) and Cherkes, Sagi and Stanton (2009) provide a significant challenge to the investor sentiment explanation of the closed end fund puzzle. Certainly their findings provide considerable support to the rational view of discounts and premiums to net asset value.

[7] See for example, Chen, Jegadeesh and Wermers (2000) and Berk and Green (2004).

1.9 The Equity Premium Puzzle

The equity premium puzzle was identified by Mehra and Prescott (1985) who show that the realised return on US equity over a period of 60 years is approximately 7.9% whilst the realised return on US treasury bills over the same period is approximately 1%. Mehra and Prescott also document similar equity premiums in the UK, Japan, Germany and France. It is argued that the equity premium is too large to be justified by the variance of returns unless investors are unrealistically risk averse. According to Mehra and Prescott the equity premium, low riskless rate of interest and smooth consumption behaviour can only be explained by an implausible degree of risk aversion. The puzzle therefore involves two central questions. Firstly, what causes such a large equity premium and secondly why would any investor choose to hold bills? In both cases investors are giving up a current and certain level of consumption for an expected higher level of future consumption. Yet in the case of bills they are willing to do so for a return of only 1%.

Siegel (1992) examines the equity premium over a much longer time period and finds that, although the return on equity has always been high, the gap between this return and the return on bonds has steadily widened due to falling returns on government fixed-income securities. Weil (1989) also notes the existence of an equity premium puzzle although presents the low rates of return on riskless securities as the main enigma.

Constantinides (1990) argues that the utility derived from consumption depends upon past levels of consumption. This dependency results in a high degree of aversion to reductions in consumption and a consequent requirement for a high equity premium. However this does not explain the divergence between equity and treasury-bill returns. The explanation also fails in the light of low direct equity investment with the majority of holdings being concentrated with high net worth individuals.

Bernartzi and Thaler (1995) published the key behavioural work on the equity premium puzzle. The central psychological traits are that investors are loss averse and evaluate their portfolios on a frequent basis. Bernartzi and Thaler refer to this combination as myopic loss aversion. They argue that prospect theory helps explain why investors demand such a large equity premium. Individuals have a high sensitivity to losses even when they do not affect consumption. The more often individuals evaluate their holdings the shorter their horizons become as they observe short-term return variability. The combined effect of risk aversion and frequent wealth monitoring is that investors demand a high equity premium.

Barberis, Huang and Santos (2001) present an explanation for the equity premium puzzle that involves investors who are loss-averse and frame assets narrowly. Hence investors frame their portfolios narrowly and perceive risk in the light of past investment decisions and outcomes. This is found to generate a time-varying risk premium that results in much greater price volatility than the volatility of related dividends. A particularly large equity premium is generated by the combination of excess volatility and loss aversion.

Constantinides, Donaldson and Mehra (2002) present the equity premium puzzle in the context of a generation gap where the young investors face borrowing constraints whilst the middle-aged investors hold diversified portfolios of stocks and bonds. In the absence of borrowing constraints the young investors would borrow and invest in equity thus narrowing the gap in premiums. The higher bond yield will then encourage middle-aged investors to re-allocate more of their portfolios to debt securities.

Although the Barberis, Huang and Santos and Bernartzi and Thaler explanations are particularly appealing from a behavioural perspective, the model of Constantinides, Donaldson and Mehra provides useful insights and contributions to the debate.

1.10 Collective Behaviour

It is important to appreciate that collective behaviour of market participants has the potential to significantly affect prices in financial markets. Prices may be pushed away from fundamental values and potential valuable private information may not be revealed if investing becomes a collective action. Galbraith (1994) and Visano (2002) provide a number of insights into the behavioural phenomenon of collective behaviour which is frequently observed in financial markets and generally follows an established pattern. A perceived new development or opportunity arises which either represents a breakthrough or advancement in knowledge. Less informed investors who observe this development are optimistic about its prospects and will be inclined to invest in it. This, in turn, attracts other investors creating a sense of euphoria which is reinforced by rising prices. The observation of rising prices further exacerbates the inclination of other investors to imitate and reinforces overconfidence in the opportunity. Once the fundamentals of the opportunity become apparent, assuming the initial expectations were over-inflated, a readjustment takes place as prices fall to the appropriate level. A clear example is provided by the technology bubble of the late 1990s which follows the classic pattern of collective behaviour.

There are two sub-categories of collective investor behaviour which have been identified in the literature; positive feedback trading and herding. Positive feedback trading is trend chasing behaviour where rising prices provide a buy signal and falling prices a sell signal. Furthermore, contrarian strategies may be interpreted as negative feedback trading. Clearly such behaviour contradicts the notion of weak-form market efficiency. Sentana and Wadhwani (1992) identify uninformed traders as key participants in collective behaviour. However De Long, Shleifer, Summers and

Waldmann (1990) and Andergassen (2005) find that rational investors, who are aware that prices may be too high, will also buy with the expectation that uninformed traders will continue to push prices further away from fundamentals. The level of analyst coverage and market manipulation may also have an impact on feedback trading.

The Sentana and Wadhwani (1992) model has been widely used to examine for the presence of positive feedback traders. Their model can be used to identify positive feedback trading and can be adjusted to analyse the relative strength of trading in rising and falling markets. Koutmos (1997) used the Sentana and Wadhwani model to investigate markets in Australia, Belgium, Germany, Italy, Japan and the UK for the period 1986-1991. His results confirmed the presence of significant positive feedback trading which generated negative return autocorrelation. Furthermore, Koutmos identified the presence of directional asymmetry. Aguirre and Saidi (1999) examined 18 series of exchange rates from EU, ASEAN and NAFTA countries for the period 1987-1997. They found evidence to indicate that exchange rate markets are characterised by significant positive and negative feedback trading. However, although there was some evidence of directional asymmetry, it was not always present. Koutmos and Saidi (2001) investigated markets in South East Asia between 1990 and 1996 and found evidence of significant positive feedback trading which generated negative return autocorrelation. They again found evidence of directional asymmetry. Watanabe (2002) investigated the Japanese market between 1976 and 1996 and found evidence to support the findings of Koutmos and Saidi. Although directional asymmetry was again present, margin trading was found to be a possible explanatory factor. Bohl and Reitz (2006) performed similar test on the German market for the period 1998-2002 and their results confirmed the presence of significant positive feedback trading which generated negative return autocorrelation.

The second sub-category of investor behaviour arises from the tendency of individuals to observe what other investors are doing and attempt to imitate them.

The recommendations of analysts, for example the internet postings discussed in the section on overconfidence, reinforces the imitative behaviour. According to Hirshleifer and Teoh (2003) herding is a behavioural similarity stemming from the interactive observations of individuals. In other words people follow those who they interact with. Bikhchandani and Sharma (2000) sub-divide herding behaviour as being either intentional or spurious. Herding behaviour may often be caused by the behavioural biases discussed in Chapter 1. For example, the representativeness heuristic identified by Barberis, Shleifer and Vishny (1998) may lead to individuals collectively (and erroneously) perceiving a price movement as representative of a trend.

Devenow and Welch (1996) argue that less sophisticated or less well-informed investors seek to benefit from mimicking the investment decisions of those seen as better-informed or privy to superior information.

Scharfstein and Stein (1990), Truman (1994) and Graham (1999) investigate managerial motives for herding behaviour. They argue that poor-performing portfolio managers will copy the decisions of better-performing managers to the extent that ultimately it becomes difficult to distinguish between the two categories. The motivation is provided to the poor-performing group by the opportunity to enhance their reputation or improve career prospects.

Herding may also be attributed to the relative homogeneity of the investment community particularly as they are likely to share common backgrounds in education and experience. This makes it likely that they will form opinions and expectations in a similar way and hence make the same or similar investment decisions. They are also likely to be driven by similar compensation packages and will be governed by the same rules and guidelines.

Christie and Huang (1995) analysed the cross-sectional dispersion of stock returns on the assertion that a lower dispersion would indicate herding behaviour as returns would be concentrated around their mean value. However, ultimately Christie and Huang found no evidence of herding during extreme market periods.

Chang, Cheng and Khorana (2000) investigated the emerging markets of Korea and Taiwan and uncovered evidence of significant herding. However, when they applied the same analysis to the more developed markets of the US, UK, Japan and Hong Kong they were unable to find any evidence of herding.

There is substantial consensus in the literature which highlights herding as more prominent in emerging as opposed to more developed financial markets. Less transparency, lax regulation and thin trading are offered as plausible explanations. Under these circumstances the quality of information is comparatively low hence the investment decisions of others are perceived as potentially a more valuable source.

Herding appears to be most prominent in the largest and smallest company shares. For large company shares this may be partly explained by index-tracking funds which are constrained in their choice of portfolio constituents. The collective buying and selling patterns when particular shares are either included or deleted from an index will appear as herding behaviour. For small company shares, the low analyst coverage discussed in Chapter 1 combined with relatively low liquidity can result in more weight being attached to peer opinion and hence reflected in herding behaviour.

A significant body of literature supports the existence of herding across financial markets and suggests that it is a key contributor to speculative bubbles. This finding further justifies investigation into the major financial crises in the first part of the 21st century.

1.11 Behavioural Corporate Finance

Behavioural corporate finance presents corporate activity such as the issue of securities, dividend policy and investment decisions as responses to mispricing in markets. What follows is a short review of some key literature in this field.

Shefrin (2001) discusses implications for directors and managers of behavioural corporate finance and argues that they need to recognise and act on impediments to long-run value maximisation. There are internal and external impediments to the traditional corporate objective. Internally, managerial behaviour is affected by cognitive biases such as overconfidence and loss-aversion. Externally the values of securities are affected by errors by analysts and investors in their assessment of fundamental value. The key to the influence of external impediments is that managers are aware that stock prices can influence investors’ perceptions about company value. Hence managers may take action aimed at creating mispricing or in response to mispricing.

Baker and Wurgler (2000) find that firms issue more equity than debt in periods prior to low market returns indicating that managers time the market with their financing decisions. They examine managerial responses to mispricing and argue that capital structure reflects the consequences of past efforts to time the market. For example initial public offerings and seasoned equity offerings occur when share prices are high and stock repurchases occur when prices are low.

Baker and Wurgler (2004) propose a catering theory of dividends which relaxes the Modigliani and Miller assumption of market efficiency. Baker and Wurgler argue that investors like to receive dividends at particular points in time. Companies cater to the preferences of investors by paying dividends when they are appreciated and omitting dividends when they are not. This is explained by a dividend premium for stocks that pay dividends which varies over time. The dividend premium is represented by a range of proxies and each proxy is found to be a significant predictor of the initiation rate of dividends. The reason for the variation is that it allows firms to take advantage of investor sentiment. Catering to time-varying demand of investors is seen by managers as a way of maximising share price.

Shleifer and Vishny (2003) construct a model of mergers and acquisitions where transactions are driven by the market valuations of the merging firms. The model is based on an inefficient market, where some firms are undervalued, but with well-informed managers who recognise inefficiencies and exploit them. In other words, managers act as arbitrageurs in an inefficient market for firms. Shleifer and Vishny also argue that managers will make a concerted effort to get their equity overvalued prior to making acquisitions of undervalued firms with stock. Hence firms with overvalued stock tend to survive and prosper whilst those with undervalued stock become takeover targets.

1.12 Speculative Bubbles

The clearest example of collective behaviour in financial markets is the phenomenon of speculative bubbles. Their existence is a direct indication of sentiment in investment decisions. Bubbles are particularly important in this study as options markets are used to examine investor behaviour over the recent technology bubble. Bubbles are not a particularly modern phenomenon. For example the tulip bulb bubble occurred in the 1630s and the South Sea bubble occurred in the 1720s.[8] The relatively recent speculative bubble was inflated by the growth of internet companies from early 1995. This, in turn was a key driver in the significant rise in the value of aggregate stock markets of major economies. Shiller (2000) borrows Alan Greenspan's term irrational exuberance to explain the internet stock bubble of the late 1990's as investors bidding up stock prices to unrealistically high levels as a result of mass market psychology. The peak of the technology bubble may be identified at the point where the NASDAQ index reached 5048.62 points. This occurred on the 11th of March 2001. Investor sentiment was clearly evident in the rush to subscribe to IPOs for internet and technology companies, many of which lacked the fundamentals to justify their valuations. Ljungqvist and Wilhelm (2003) find that in 1999 average first day returns for all stocks stood at 73% but had fallen to 58% by 2000. In contrast, first day returns for internet stocks during1999 and 2000 stood at 89%. The bubble burst as investor confidence was eroded by subsequent poor company performance. This was reflected in the decline of the NASDAQ to a level of just over 1100 points by October 2002. Sharma, Easterwood and Kumar (2006) attribute the bubble to herding amongst institutional investors.

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[8] Chancellor (2000) provides a thorough account of these early bubbles.

Johansen and Sornette (2001), in a study of bubbles in emerging markets, characterise speculative bubbles as following a life-cycle. In its early stages the bubble begins relatively smoothly but with increasing demand for assets in a predominantly bullish market. The potential to achieve significant gains attracts new investment which is often supported by high levels of leverage. Less sophisticated investors observe the upward trend and join in. Market prices then begin to diverge significantly from fundamental values. As the price peaks the number of new investors decreases and market turbulence increases ultimately leading to its collapse.

The price of any asset during a bubble period will be made up of fundamental value, given by the present value of future cash flows, plus a bubble component. However testing for bubbles empirically is not possible as observed fundamentals *ex post* provide an inappropriate proxy for expected future cash flows *ex ante*. Even in cases where stocks are observed to have been massively overpriced relative to realised cash flows there is often a non-zero probability that at some point in the future the companies may generate returns that will justify the high valuations.

Numerous sources of bubbles have been identified in the literature. Shiller (1984) argues that bubbles occur as a result of mass psychology and the interaction of sophisticated and unsophisticated investors. Shiller argues that the market contains much fewer sophisticated investors than is usually assumed and instead is heavily populated by investors who are susceptible to trends and fads. Shiller tests his proposals using the S&P Composite stock index to demonstrate that stock prices overreact to dividends and these mispricings are not eliminated by sophisticated investors.

De Long, Shleifer, Summers and Waldmann (1990) argue that irrational optimistic noise traders contribute to bubbles by pushing prices away from fundamental value. Because noise trader sentiment is very unpredictable the level of risk faced by potential arbitrageurs deters them from entering the market to eliminate price discrepancies. Essentially arbitrageurs with short time horizons are unwilling to bear fundamental risk allowing noise traders to earn increased returns as a result of destabilising the market. De Long *et al* follow Black (1986) in asserting that noise traders trade on the basis of noise as if it were information.

Bubbles are identified as rational by Flood and Hodrick (1990), Allen and Gorton (1991) and Montier (2004). Allen and Gorton distinguish between fund managers who are able to correctly identify undervalued firms and those who cannot. Those who are unable to identify undervalued firms buy into trends anyway as they are rewarded for achieving positive returns. This is a rational strategy if they have the potential to achieve rewards from the upside but do not share in the downside risk. Flood and Hodrick argue that bubbles are driven by positive feedback trading hence a rising current price is a signal of a higher future price even if the stock is currently trading above fundamental value. Montier notes that rational investors recognise the existence of a bubble and assess the probability of it bursting in a given period. This determines whether they remain in the market or get out. Remaining in the market is highly risky but contributes to the inflation of the bubble.

Ofek and Richardson (2003) consider the dot com bubble and note that there were frequent arbitrage opportunities available. They pose the question why, when technology stock prices were clearly irrationally high, did rational traders fail to short these stocks and restore prices to their fundamental values. Ofek and Richardson note that, during this period, investors were unable to borrow sufficient stocks to sell short at a reasonable cost. Thus non-regulatory short sales constraints resulted in limited arbitrage.

1.13 Investor Behaviour and Moods

A number of relatively recent studies have analysed the impact of investors' mood on investment decision making. More precisely, studies seek to establish whether mood factors have explanatory power for financial anomalies.

Schwarz and Clore (1983) produced the seminal work investigating the influence of mood on the happiness and satisfaction of individuals. Misattribution bias is examined by Schwarz and Clore who find that if mood is misattributed to another source the negative feelings that cause the dissatisfaction can be eliminated. They propose that incorrect judgements arise when individuals mistakenly attribute their feelings to inappropriate sources. For example, a happier, more positive outlook during periods of good weather may be misattributed to a perception of positive life prospects. Ariel (1990) examines US stock returns prior to holidays and finds that they are higher than normal. This is attributed to a positive investor outlook in anticipation of a holiday. Forgas (1995) asserts that the mood effect will be more powerful when relevant information is characterised by complexity and uncertainty. The impact is likely to be considerably stronger on unsophisticated investors compared to on professional traders.

Schwarz and Bless (1991) and Shu (2010) argue that positive mood leads to optimism and reduces risk aversion. Investors with a positive demeanour are therefore more likely to make decisions based on the type of heuristics presented in Chapter 1. Good mood is also likely to increase the possibility that that the volume of investment will increase and should therefore be associated with rising prices.

Wright and Bower (1992) argue that investors who are in a good mood will assign relatively high probabilities to positive outcomes. This leads them to underestimate risk and hence invest in risky assets. Such investment behaviour means that the investor faces volatile returns and potential subsequent poor performance. Likewise, Kamstra, Kramer and Levi (2003) suggest that bad moods will decrease the likelihood of investing in risky assets. This is particularly the case in autumn and winter when there are fewer hours of daylight. Petty, Gleicher and Baker (1991) add that negative emotions are usually associated with more in depth analysis and evaluation of information, less risk-taking and generally better decision-making.

It is well-documented that sunshine makes people feel good which in turn will make them feel optimistic about investment decisions. The other side of the coin is that a lack of sunshine is linked to low mood and depression. Saunders (1993) finds that returns on the New York Stock Exchange and on the American Stock Exchange are strongly linked to the level of cloud cover, adding support to the relationship between sunshine and investor mood. Hirshleifer and Shumway (2003) apply the psychological evidence in order to examine the impact of sunshine on the stock market returns of 26 countries. The sunshine must be in the city where the stock exchange is located and the degree of cloudiness is measured against the expected degree of cloudiness for the time of the year. This controls for any seasonal effects on stock market returns. Hirshleifer and Shumway conclude that sunshine has a strong positive relationship with stock market returns but no negative relationship is detected with inclement weather. Other weather effects are found by Krivelyova and Robotti (2003) who find that geomagnetic storms have a negative effect on US stock market index returns. The result is robust when applied to most other international markets. Cao and Wei (2005) hypothesise that lower temperatures are related to aggression and risk taking and therefore should result in higher returns. They find results from global markets to support this hypothesis and also that warm weather leads to apathy and hence lower returns.

The impact of lunar cycles on the performance of global stock markets was analysed by Yuan, Zheng and Zhu (2006). It is posited that the full moon is correlated with low mood. Yuan *et al* find that stock returns were consistently and significantly lower around a full moon than around a new moon. The effect is also found to be strongest in developing markets.

There are some studies that investigate the effects of social events on investor behaviour. In particular, negative stock market reactions to defeats in football matches are examined.[9] Edmans, Garcia and Norli (2007) looked at the returns on stock markets following the respective country's performance in an international football match. Negative returns were observed the day after the match. Negative returns were found to be larger if the match was more important and also if the country concerned was a traditionally strong footballing nation. Interestingly, there was no relationship found between victories and stock returns. Similar effects were found when investigating a variety of other sports. Klein, Zwergel and Heiden (2009) produce results which contradict those of Edmans *et al*. Klein *et al* investigate World Cup and European Championship matches between 1990 and 2006 and benchmark index returns for 14 European countries. Games were also categorised as to how expected a particular result would be. Klein *et al* were unable to produce evidence that the result of a match, however unexpected, had an influence on aggregate stock market returns.

[9] The author, a long time supporter of Newcastle United F.C., has considerable experience in this respect!

This brief literature review on the impact of investor moods on stock market returns provides some support for the notion that markets move for reasons other than information. This further supports the justification for the behavioural finance paradigm and casts further doubt on neoclassical finance.

1.14 Future Directions of Behavioural Finance

1.14.1 Stock Markets

The models that have been offered to date are restricted in the sense that they generally incorporate only one of the three key areas; investors' beliefs, investors' preferences and limits to arbitrage. Possible future research could extend behavioural models to incorporate more than one of these three areas.

There are numerous competing theoretical behavioural explanations of some of the empirical evidence. These theories will be more compelling if more models can be formulated with testable implications. Empirical tests must be capable of comparing and contrasting these behavioural theories with those that underpin neoclassical finance.

It will also be useful to search for evidence which identifies whether agents within financial markets actually behave in the way behavioural models suggest they do.

Financial crises, accounting scandals and other events that have occurred in recent years have made observers increasingly sceptical of the efficient markets hypothesis and the neoclassical paradigm. Hence the opportunity is presented for proponents of behavioural finance to examine how human behaviour and rigidities result in a market which is less than efficient.

1.14.2 Derivative Markets

The overwhelming majority of the behavioural finance literature to date focuses on the markets for underlying securities. In particular, stock market data is readily available, accurate and lends itself well to empirical analysis. Much less analysis has been focused on the derivative securities which are written on the underlying assets. This is presumably because derivatives are regarded as redundant assets. An interesting addition to the behavioural finance literature would therefore be to drop that assumption. Some studies have been published that analyse the role that derivatives have to play in this topical and evolving branch of finance. Such examination is underpinned by a rejection of the notion that derivatives, and in particular options, are redundant assets. This study will attempt to contribute to the existing body of literature by investigating some of the behavioural issues involving options markets.

1.14.3 Key Criticisms of Behavioural Finance

Proponents of traditional finance present a number of criticisms of behavioural finance. The future of the behavioural finance paradigm rests on being able to answer these criticisms. Common objections are that the models are rather ad hoc or simply not testable. Furthermore, any tests which are performed are criticised for involving data mining. Behavioural finance is also dismissed as possessing no unified theory. Subrahmanyam (2007) provides a counter argument that the models that have been proposed are based on human behaviour and can explain the evidence. He also argues that the data mining accusation is simply not true. Furthermore, it is better to focus on theories consistent with the evidence rather than rational economic theories with limited empirical support. If people in general, and investors in particular, do not conform to the concept of rationality then assuming they are rational is dubious in terms of understanding financial phenomena.

1.14.4 The Next Paradigm?

Behavioural Finance is no longer a new approach. Indeed its roots are in the 1970s and 1980s. The debate between the rational and behavioural approaches continues but behavioural finance suffers from being unable to produce an asset pricing model.

The next paradigm could well be one which presents the market as a considerably more complex place populated by heterogeneous participants. Mauboussin (2002) and Farmer (2002) provide important research into evolutionary finance. Evolutionary finance considers adaptive agents in financial markets who compete tactically in light of evolving circumstances. Investors continuously evaluate trades and update their portfolios accordingly so that each investor evolves as part of a pool. The interaction of the trading strategies of heterogeneous agents over time results in a recurring cycle of feedback, processing, decisions, investment, price information and adaptation. Evolutionary finance appears to provide a fertile opportunity for future research.

1.15 Conclusion

This chapter has provided an extensive critical review of the vast body of literature published in the field of behavioural finance. It has been demonstrated that the behavioural finance paradigm presents a significant challenge to neoclassical finance in general and the efficient markets hypothesis in particular. The findings of this chapter provide ample motivation for an in-depth evaluation of literature which examines for the influence of behavioural finance in options markets. This evaluation in turn is expected to provide motivation for further empirical analysis using options data.

Chapter 2

Behavioural Finance and Options Markets

2.1 Introduction

A number of important theoretical and empirical challenges to the efficient markets hypothesis have been identified in the literature. One consequence of the dissatisfaction with EMH is the expanding body of literature reviewed in the previous section. This literature, for the most part, is focused on equity markets, whilst there is apparently little attention given to derivative markets. One obvious reason for the relatively sparse behavioural literature on options markets is that, where arbitrage is not limited, option prices can be fixed in relation to the prices of underlying and riskless assets. As a consequence option prices should not contain any additional information. However if arbitrage is limited, as in Shleifer (2000), then other factors such as demand and supply may affect option prices. This, in turn, means that option prices could contain additional information to that found in equities and provides motivation to examine the literature related to options markets. Furthermore, it is important to establish whether research into options markets is able to produce empirical evidence which provides support to the behavioural finance paradigm.

This section examines some of the key early literature in six main areas which form a basis for more recent developments and the subsequent empirical work in this thesis. The options market tests are sub-divided as follows; the violation of rational pricing bounds, the robustness of the put-call parity relationship, the deviation of market prices from model-determined theoretical prices, misreaction to information, demand and momentum, irrational early-exercise and trading behaviour.

2.2 Violations of Rational Pricing Bounds

Merton (1973) built on the work of Stoll (1969) to produce a highly influential paper which derived theoretical upper and lower pricing bounds for European-style put and call options. Merton argued that under conditions of riskless and frictionless arbitrage the pricing bounds should not be violated. Importantly, the bounds which were derived, presented below, do not depend on any assumptions about the key factors known to affect option price nor on any assumptions about the stochastic process followed by the asset underlying the option contract. European-style options are in lower case and American-style in upper case.

Call upper bound

$$c \leq S_0, \; C \leq S_0 \tag{2.1}$$

Call lower bound (Non-Dividend Paying Stock)

$$c \geq (S_0 - Ke^{-rT})^+ \tag{2.2}$$

With Dividends

$$c \geq (S_0 - D - Ke^{-rT})^+ \tag{2.3}$$

Put upper bound

$$p \leq Ke^{-rT}, \; P \leq K \tag{2.4}$$

Put lower bound (Non-Dividend Paying Stock)

$$p \geq (Ke^{-rT} - S_0)^+ \tag{2.5}$$

With Dividends

$$p \geq (D + Ke^{-rT} - S_0)^+ \tag{2.6}$$

Galai (1978) performed *ex ante* tests of the lower boundary conditions of call options listed on the CBOE using daily prices for the period of April to November 1973. Galai also tested for the synchronicity of options trading with trading on the associated underlying assets. Galai notes that violations of the option pricing bounds do not necessarily indicate an exploitable arbitrage opportunity as the arbitrageur must first identify the mispricing then execute trades in two markets in order to exploit it. There is no guarantee that the next price move will be in the arbitrageur's favour. Furthermore, results should be interpreted with caution, as closing prices at this time reflected the last trade to take place in a market which was much less liquid than the current options market. Galai finds numerous violations of the boundary conditions *ex post* but concludes that any 'arbitrage' profits are subject to considerable uncertainty *ex ante*. Hence profitable opportunities are reduced considerably or disappear altogether. Moreover, his finding of non-synchronised trading further reduced the probability of exploiting violations of the boundary conditions.

Bhattacharya (1983) performed tests of the efficiency of options traded on the CBOE using transactions data from August 1976 to June 1977. His tests focused on violations of the options pricing bounds proposed by Merton (1973) and Galai (1978) and on relative mispricing of calls with different strike prices but all else equal. Bhattacharya found that there were some small but infrequent violations of pricing bounds however there were no positive returns to be earned once transactions costs were included. More violations were found when the calls with different strike prices were paired into spreads however it remained unclear as to whether the violations were exploitable.

2.3 Violations of Put-Call Parity

Merton (1973) extended the option pricing bounds presented above to produce the now well-established put-call parity condition. Put-call parity demonstrates that the price of a European-style put can be deduced from that of a European-style call written on the same underlying asset, with the same strike price and with identical maturity dates:

Non-Dividend Paying Stock

$$c + Ke^{-rT} = p + S_0 \tag{2.7}$$

With Dividends

$$c + D + Ke^{-rT} = p + S_0 \tag{2.8}$$

The condition does not apply to American-style options, however a similar relationship holds which identifies a range in which an option price must lie:

Non-Dividend Paying Stock

$$S_0 - K \leq C - P \leq S_0 - Ke^{-rT} \tag{2.9}$$

With Dividends

$$S_0 - D - K \leq C - P \leq S_0 - Ke^{-rT} \tag{2.10}$$

The put-call parity relationship is a no-arbitrage relationship involving options and their underlying stocks and is derived under the assumption that investors are able to short-sell these stocks.

Gould and Galai (1974) examine the hedged positions that need to be constructed which will theoretically yield a riskless rate of return. The objective of Gould and

Galai's work was to establish the transactions costs associated with constructing a hedged position. These transactions costs have the effect of extending the boundary conditions.

Klemkosky and Resnick (1979) test for put-call parity using options traded on the CBOE between 1977 and 1978. Initially the market appears to be inefficient as numerous violations of put-call parity are discovered. However Klemkosky and Resnick (1980) recognise that their earlier work was biased due to non-synchronous trading and transactions costs. Once adjustments are made to allow for these effects any potential arbitrage opportunities disappeared. Similar issues are illustrated by Bodurtha and Courtadon (1986) in the currency options market.

Loudon (1988) analyses options traded on a single Australian stock, Broken Hill Proprietary Company Limited, during takeover activity in 1985. The justification for focusing on a single company is that intense option trading took place during the takeover period hence this offered the best opportunity for obtaining simultaneous price data. The availability of simultaneous price data allows Loudon to construct a robust test of put-call parity. The options are American-style so a relationship equivalent to that presented in equation (2.9) is tested. Loudon finds some violations, particularly of the lower option pricing bound. However these violations were not exploitable due to transactions costs consisting mainly of institutional restrictions.

Nisbet (1992) examines the efficiency of the UK options market using transactions data from June to December 1988. As these are single stock options they are American-style and hence contain the added complication of the possibility of early exercise. Nisbet finds a substantial number of *ex ante* profitable opportunities arising from put-call parity violations however over half of these are eliminated following adjustments for transactions costs arising from the bid-ask spread. Furthermore it is noted that exploiting these opportunities in practice will be severely limited by short selling restrictions and the potential for early exercise of American-style options. Kamara and Miller (1995) analyse S&P 500 stock index options and find that less violations are apparent than identified in earlier studies on individual equity options. Lamont and Thaler (2003) posit that different investors populate the options market than populate the equity market. This separation of investors means that irrationality in the equity market does not necessarily imply irrationality in the options market. It is therefore possible, under conditions of limited arbitrage that, at any given time, the market price of a stock may differ considerably from the price implied by the premium of an option written on that stock. Lamont and Thaler analyse the stocks of three companies that have been subject to an equity carve-out, where the market value of the parent company is less than the value of its ownership in the carve out. These mispricings are presented as clear evidence of limited arbitrage caused by impediments to short-selling.

Ofek, Richardson and Whitelaw (2004) use OptionMetrics data from 1999 to 2001 to investigate efficient option pricing when short-selling of the underlying stocks is restricted. They find that the magnitude of put-call parity violations increase with the rebate spread. The rebate spread is used to measure the cost and difficulty of short-selling and is given as the rate earned from the proceeds of a short-sale minus the standard rate. Ofek *et al* find a significant negative relationship between the rebate rate and the size of violations where rebate rates are negative, which is approximately 31% of the time. Ofek, Richardson and Whitelaw's findings are consistent with the behavioural finance perspective of irrational investors in the equity market pushing prices away from fundamental value and the mispricings persisting due to short-sales limiting arbitrage. Furthermore, Ofek Richardson and Whitelaw find that put call parity violations have significant predictive power for future stock returns.

2.4 Deviations of Market Prices from Theoretical Prices

Early empirical tests of option market efficiency were carried out by Black and Scholes (1972) who found evidence of systematic deviations of market prices from theoretical prices. In particular, Black and Scholes found that deep in-the-money-options tended to be overpriced and deep out-of-the-money options tended to be underpriced.

Finnerty (1978) analysed the efficiency of options listed on the Chicago Board Options Exchange (CBOE). Finnerty uses options and underlying asset data from 1973 to 1974 to produce a riskless portfolio which is rebalanced weekly. He finds results to confirm Black and Scholes' assertion that the model tends to overprice options on high variance securities and underprice those on low variance securities.

Galai (1977) also analyses CBOE data in testing for market efficiency. Galai performs *ex post* and *ex ante* equilibrium tests on a riskless Black-Scholes hedged portfolio of stocks and options. The former investigates the potential for the Black-Scholes to produce abnormal profits whilst the latter investigates whether a trader will be able to purchase profitable hedged positions in practice. Galai recognises the joint hypothesis problem but continues on the assumption that the Black-Scholes model is 'correct'. Some deviations are found both *ex post* and *ex ante* however these did not appear to be exploitable

2.5 Overreaction and Underreaction in Options Markets

Important evidence has been produced indicating that overreaction occurs in options markets. Early contributions were provided by Stein (1989) and relatively more recently by Poteshman (2001). Poteshman provides some support for the findings of Stein and also finds evidence of underreaction and increasing misreaction which he rationalises in the context of the investor sentiment model of Barberis, Shleifer and Vishny (1998).

Stein (1989) posits that evidence of traders' overreaction to new information may be found in the S&P100 options market. Although traditional option pricing theory suggests that, under the assumption of constant volatility, option prices are fixed by arbitrage considerations, this will not necessarily be the case when volatility cannot be directly observed, must be estimated and is changing. Thus options will retain a component that is independent of the price of the underlying asset. Stein argues that options may be considered as reflecting a speculative market in volatility. An option's implied volatility ought to equal the average volatility that is expected to prevail over its life. It follows that term structure tests can be performed to assess if the structure of implied volatilities over time is consistent with rational expectations. For example, if volatility is mean-reverting an implied volatility above this mean for a short-dated option should be countered by a lower implied volatility for the next shortest dated option and vice versa. Stein's evidence contradicts this rational expectations view in that, although volatility shocks decay rapidly, market participants do not take this fully into account when pricing options. Less smoothing across implied volatilities extracted from options of different maturities is found than anticipated and long-term options overreact relative to short-term. The implication is that market participants believe that a relatively small number of innovations in short-term options' implied volatility are representative of the temporal structure. In practice practice market participants should attach more weight to historical data that suggest that these innovations will not persist.

Although the mispricings identified are not of the magnitude that may occur with stocks or bonds, they are interpreted as having strong implications. The only uncertain variable in option pricing is volatility whereas the prices of primary securities, such as stocks, contain risk premia. The pricing of risk premia means that irrational excess variability in the stock and bond markets may be interpreted as rational market responses to time-varying equilibrium rates of return. Since required rates of return are not observable, it is difficult to reach a definitive conclusion. The arbitrage conditions underpinning option prices should allow options to be priced independent of risk and therefore they should not suffer from this ambiguity. In addition, mispricing in options pinpoints overreaction to new information as the specific cause of excess fluctuations. Much of the literature on inefficient capital markets is unable to be so specific in identifying a cause. Indeed, when traders are pricing long-term options their best and clearest source of information is the implied volatility of the respective shorter-term option. The remaining inputs are the, easily objectively quantified, parameters of the process driving volatility. This is in sharp contrast to the large, often subjective, information necessary for the correct pricing of stocks. Because of this comparison, Stein suggests that it is tempting to suppose that simplistic and perhaps overreactive rules of thumb must be of fundamental importance in the stock market.

Essentially Stein employs two types of tests of the joint hypothesis that the pricing model used to recover implied volatilities is correct and that volatility expectations are formed rationally. He uses daily observations on implied volatility for S&P 100

(OEX) index options for the period December 1983 to September 1987. There are two series, which Stein terms nearby and distant. The nearby series are the nearest options to maturity whilst the distant options have the next maturity. This means that each series have maturities that are one month apart. Implied volatility is taken as the average of that of the closest to the money puts and calls. The binomial model of Cox, Ross and Rubinstein (1979) that accounts for early exercise and the dividend yield is used for the calculations.[10] Stein uses daily closing prices of the options and the index.

Using close to the money options reduces the likelihood of any problems of biases resulting from stochastic volatility. Stein asserts that the prices of at the money or close to the money options are almost exactly linear in volatility at all maturities. He continues to state that implied volatilities derived from the Cox, Ross and Rubinstein model should accurately reflect the average volatility that is likely to prevail over the life of the options. Stein also emphasises that pricing biases alone would not be sufficient to produce false acceptances of overreactions in his tests.

The key conclusion from Stein's model-dependent study is that, under the assumption that the Cox, Ross and Rubinstein option pricing model is correct, there is clear evidence of consistent overreaction in the term structure of implied volatility.

Poteshman (2001) investigates options market reaction to changes in the instantaneous variance of the underlying asset. His overall objective is to investigate the options market for evidence of investor misreaction similar to that found in the equity market; i.e. where investors underreact to information over short horizons and overreact to information over long horizons. More specifically Poteshman examines

[10] A derivation of the Cox, Ross and Rubinstein model is presented in Appendix 1.

whether investors in options markets underreact to information contained in daily changes in instantaneous variance over short horizons and to find if the long horizon overreaction presented by Stein (1989) in the S&P 100 options market is present in the S&P 500 options market during a more recent period. He argues that his evidence is consistent with that from stock markets and significantly contributes to the debate on investor misreaction by employing options market data. Furthermore, Poteshman commends options data as providing ideal opportunities to move the debate forward. This commendation is supported using three important arguments: the primary importance of instantaneous variance of the underlying asset in option pricing; the apparent lack of empirical literature that examines the reaction of options market investors to information that follows a stream of similar information; the high degree of liquidity of the S&P 500 options market and the sophistication of investors which jointly contribute to providing a high quality data set.

The Barberis, Shleifer and Vishny (1998) model, outlined in Chapter 1, reconciles short horizon underreaction and long horizon overreaction where investors are subject to conservatism and the representativeness heuristic. Investors underreact to individual pieces of information but interpret periods of similar information as indicative of a trend. Although conservatism causes unconditional underreaction to individual pieces of information, interaction with the representative heuristic means that the investor tends to underreact to information that follows a relatively small quantity of similar information and to overreact to information preceded by a relatively large quantity of similar information. The theoretical mechanism devised by Barberis, Shleifer and Vishny underpins the options market analysis of Poteshman (2001).

Poteshman examines exchange-traded options to establish whether options market investors tend to underreact (overreact) to current daily changes in instantaneous variance that are preceded mostly by daily changes in instantaneous variances of the opposite (same) sign. The transactions data relates to options traded on the CBOE for a ten year sample period which runs from 1988 to 1997. The results are produced by using the stochastic volatility model of Heston (1993) which generalises the Black-Scholes-Merton model while retaining the relationship between the distribution of spot returns and the cross-sectional properties of option prices and provides a closed-form solution for options on assets with stochastic volatility.[11] Poteshman cites Bakshi, Cao and Chen (1997) and Chernov and Ghysels (2000) to support his selection of the Heston model.

Bakshi, Cao and Chen (1997) investigate the improvements on Black-Scholes pricing of European-style S&P 500 call options that can be achieved by incorporating stochastic volatility, jump-diffusion and stochastic interest rates. They find that little improvement on their stochastic volatility-jump diffusion model can be achieved by incorporating stochastic interest rates. Furthermore, for hedging purposes, the best performance is achieved by stochastic volatility alone. Bakshi *et al* conclude that the stochastic volatility-jump diffusion model outperforms other stochastic volatility models and the Black Scholes model with respect to accuracy of option pricing and hedging. However, the findings of Bakshi *et al* are criticised in the literature, in particular by Bollen and Whaley (2004), as a number of their parameter estimates are significantly different to those estimated directly from the index returns.

Chernov and Ghysels (2000) investigate jointly the risk-neutral measure of derivative pricing and modelling of the behaviour of the underlying asset, using the S&P 500

[11] The Heston model is briefly presented in Appendix 2.

index and associated option contract. Although their work is not explicitly focused on a particular model they do employ the Heston model extensively, mainly because it has the advantage of providing analytic solutions. Chernov and Ghysels estimate the model by finding parameter values that minimise the sum of the squared option pricing errors. They find that the Heston model outperforms other models, such as GARCH, in terms of option pricing. It is however criticised due to its assumptions of constant interest and dividend rates. The problem of non-synchronicity of index and option values and the incorporation of the expected future rate of dividend payments is addressed by creating a dividend-discounted spot price which serves as the underlying asset value. Poteshman adopts the approach of Chernov and Ghysels (2000) in estimating the Heston model by finding parameter values that minimise the sum of the squared option pricing errors. This is then used to produce a daily time series instantaneous variances for each Wednesday in the sample period. The instantaneous variance is a parameter of the diffusion process in the Heston model. The market price of volatility risk is proportional to instantaneous variance in this model. The unexpected change in instantaneous variance is then estimated by subtracting the expected change from the actual change. Poteshman constructs three statistics to investigate misreaction.

The first statistic is used to examine the extent to which the unexpected change in instantaneous variance is overprojected into the far future relative to the near future. He finds that where the actual change is greater than the expected change, the change in the instantaneous variance of short maturity options exceeds that of long maturity options. Where the actual change is less than the expected change, the change in the instantaneous variance of long maturity options exceeds that of short maturity options. This finding is interpreted as the unexpected change in volatility being under projected into the far relative to the near future and hence consistent with short-horizon underreaction.

The second statistic is constructed to examine if the difference between the instantaneous variances implied by long maturity options and that implied by short maturity options is increasing in the level of instantaneous variance. This is found to be the case and is interpreted as evidence of long horizon overreaction to similar shocks in instantaneous variance amongst options investors.

Perhaps the most interesting results are produced following examination of a third statistic which measures the quantity of previous similar information on changes in instantaneous variance. A regression is run to measure the unexpected change in instantaneous variance conditional on the quantity of previous similar information. Poteshman finds statistically significant evidence of increasing investor misreaction to information.

All of the tau tests performed by Poteshman indicate significant results which accord with his hypotheses. Hence Poteshman is successful in moving the debate on overreaction in options markets forward.

Cao, Li and Yu (2005) build on the work of Poteshman by examining S&P 500 options and long-maturity S&P 500 LEAPS[12] for misreaction and to test whether trading strategies can be constructed which yield economically significant abnormal returns. Cao, Li and Yu use the variance shocks of the short-term options to predict the prices of longer-term options. It is found that when pricing all of the long-term options in their sample, investors underreact to short-term variance shocks. However, when there is a run of four consecutive variance shocks of the same sign

[12] LEAPS, or long-term equity anticipation securities are options with expiry dates of up to 39 months.

in short-term options, investors' reaction to these shocks increases. Momentum strategies are constructed to test whether these findings are exploitable. The momentum strategies outperform a benchmark return by between 1% and 3% although these trading profits disappear when transactions costs are taken into consideration.

Although Stein (1989) and Poteshman (2001) produce some evidence of investor misreaction in options markets they say little about the development of option pricing in terms of additional parameters. Indeed Bates (2003) notes that new approaches to option pricing are required which consider the risks faced by market-makers. The failure to significantly improve on the Black-Scholes-Merton approach motivates an investigation into the role of demand pressure in option pricing. Previously, most of the improvements in option pricing have been achieved by modelling the stochastic process followed by the underlying asset.

It is clear that a body of evidence has been published which supports the notion that options markets are similar to equity markets in that evidence of underreaction, overreaction and increasing misreaction has been uncovered. However, demonstrating that these findings result in economically exploitable opportunities is more problematic.

2.6 Momentum Effects and the Demand Parameter in Option Pricing

A growing body of literature examines whether additional parameters to those included in traditional pricing models are important in option pricing. This is partly driven by evidence of different expensiveness of, and differential returns on put and call options. For example, Coval and Shumway (2001) find that the expected returns on S&P500 index options are negative whilst those on the corresponding calls are positive. Constantinedes, Jackwerth and Savov (2011) find that returns on S&P500 options are a function of strike price. They identify out-of-the-money put volume and changes in the VIX as key factors and link these to mutual fund demand for portfolio insurance and speculative demand for leveraged equity positions.

Amin, Coval and Seyhun (2004) introduce demand as a parameter in option pricing by examining the relationship between stock price momentum and option prices.

The key objective of Amin *et al* is to examine for a divergence between call and put prices as a function of past stock returns. More specifically they analyse S&P100 options to establish whether investors bid up call prices following a stream of positive market returns and bid up put prices following a stream of negative market returns. They note that standard option pricing models do not allow for factors such as expected future returns on the underlying asset to be priced. However, in imperfect markets it is not straightforward to replicate option payoffs using the underlying asset and a risk-free asset and, as a consequence, option prices can deviate from the price of the associated replicating portfolio. It is argued that, if markets are imperfect, then option prices will be determined by supply and demand under conditions of limited arbitrage. This in turn implies that additional factors such as market momentum may have an important role in option pricing. It is proposed that stock market momentum will affect investor expectations about future stock returns and consequently influence the supply of and demand for options. Momentum will also influence investor demand for portfolio insurance.

Investors who perceive a stream of past positive returns as indicative of a trend can seek to exploit this trend by purchasing call options. As a result upward pressure is created on call option prices. Conversely, a stream of negative past returns can lead to upward pressure on put option prices. If the degree of desired exposure to stock prices depends upon recent stock market movements, then investors may turn to index options to provide a relatively cheap and easy way to achieve and adjust broad market exposure.

Amin *et al* divide their analysis by adopting two distinct approaches. Firstly they examine for put-call parity violations in S&P100 options as a function of past stock returns over the period 1983-1995. Importantly they examine whether the boundary conditions are violated more frequently after stock price increases or decreases. They find that 60-day absolute stock price changes of 5% or more, significantly increase the probability that put-call parity will be violated. Following 60-day stock market increases calls become overpriced relative to puts and vice versa for decreases.

Amin *et al* also evaluate boundary conditions across the period surrounding the 1987 stock market crash. Their results are similar to those over the entire period although the results are weaker, but remain statistically significant, in the post-crash period.

Amin *et al's* initial results illustrate that the probability of boundary violations, and the magnitude of these violations, depend upon past stock returns. They conclude that their results provide support for the market momentum hypothesis and are robust to inclusion of transactions costs in the form of the bid-ask spread. However this first set of tests do not indicate whether price pressure affects option prices generally or only under more extreme market conditions. This is addressed by their parametric approach.

Amin *et al's* second approach is to employ parametric tests to examine whether the magnitude of the violations of put call parity are affected by past stock returns and to examine whether the market momentum hypothesis holds for parametric specifications of option prices. In the parametric tests they measure the overpricing of calls relative to puts by constructing a volatility spread which is simply the implied volatility of a call option minus the implied volatility of the corresponding put option with identical contract specifications. They regress the volatility spread on 60-day past stock returns and find that this produces positive coefficients, indicating that the volatility spread increases following stock market increases and decreases following stock market decreases. Negative returns are found to lead to increased implied volatility across all options although this is most pronounced for those of short maturity and deep in or out of the money. The authors recognise that this is consistent with commonly observed implied volatility skews. Falling stock prices increase put implied volatilities more than those of calls hence puts become relatively more expensive. When stock prices rise, the prices of calls increase relative to those of puts.

Amin *et al* find that declines in stock prices more than double volatility smiles and they interpret this finding as evidence that price pressure is particularly strong for options that are away from the money. Further, they suggest that investors highly value these options in bull and bear markets and that past stock returns are likely to have explanatory power for volatility smiles. Amin *et al* also examine the volatility spread as a function of maturity and percent of moneyness.[13] They find that the decline in the volatility spread that follows declines in stock prices is robust with respect to moneyness.

Past stock returns continue to show up with a positive coefficient against the volatility spread when additional variables are included in the regression. This suggests that

[13] Percent of moneyness is defined as the percent by which the option's strike price is in the money relative to the opening level of the index.

investors' expectations about future returns directly affect their index option valuations, regardless of other influences. However, the inclusion of expectations about increased stock return volatility is found to reduce the volatility spread. This is interpreted as consistent with a scenario where portfolio insurance considerations play a role which is independent from the market momentum explanation.

Amin *et al* offer a plausible set of explanations for their findings. Central to their argument is the market momentum hypothesis where investors project past stock returns into the future and bid up put or call prices accordingly. It follows that the hypothesis predicts a positive influence of past stock returns on the volatility spread. Nevertheless, it may be the case that past stock returns act as a proxy for an omitted variable such as the negative relationship between stock returns and volatility. Hence the supply of and demand for options is affected by a combination of return expectations and portfolio insurance considerations. When volatility is high, investors desire reduced stock market exposure and bid up put option prices. When volatility falls, investors desire increased stock market exposure bidding up call prices.

Amin *et al* do not consider whether the finding of momentum effects is likely to provide an opportunity for investors to identify unexploited arbitrage opportunities. However it is emphasised that this is not the purpose of the study. The key objective here is to identify pressures on option prices. Nevertheless, considerable emphasis is placed on the implications for investors. In particular, following large stock price increases, speculation on further stock price increases are more expensive to implement using call options. The authors conclude that it would be better for investors to speculate using stocks or futures rather than options.

In contrast to Amin *et al* Cremers and Weinbaum (2010), find that implied volatility spreads provide information about future stock prices. Cremers and Weinbaum extract implied volatility spreads from US equity option data to demonstrate that stocks with relatively expensive calls written on them outperform those with relatively expensive puts. They also find abnormal positive and negative returns, particularly for firms where there is a high degree of asymmetric information.

Bollen and Whaley (2004) examine S&P500 options and 20 individual stock options[14], from June 1988 through December 2000, in order to assess the role of supply and demand in the options market. They do this by investigating the relationship between net buying pressure[15] and the shape of the implied volatility function. Bollen and Whaley's results demonstrate that, during their sample period, most trading in stock options involves calls whilst most trading in index options involves puts. Hence their demand driven model involves examination of the difference between the slopes of the call and put implied volatility functions in response to net buying pressure.

Bollen and Whaley demonstrate that investor demand affects the steepness of the implied volatility function. Furthermore, they find that significant abnormal returns are available by constructing a delta-neutral strategy which involves writing index put options. Out-of-the-money puts are found to be the most profitable. However, even before transactions costs, they find it impossible to systematically profit from a similar strategy which involves writing options on individual stocks. Bollen and Whaley establish a relationship between deviations of the implied volatility function

[14] The 20 stock options selected are traded continuously throughout the sample period and are the most liquid.
[15] Net buying pressure is defined as the difference between the number of buyer-motivated contracts and number of seller-motivated contracts traded each day according to whether they are executed above or below the bid/ask midpoint.

from realised volatility and profitability of the delta-neutral strategy. This deviation is also linked to investor demand for options adding support to their net buying pressure hypothesis under conditions of limited arbitrage.

A key weakness of Bollen and Whaley's analysis is that, in order to examine whether traders can systematically profit by constructing delta-hedged positions, they unconditionally write liquid puts and calls. In practice, an informed option trader would write puts and calls conditional on recent stock performance in order to profit from overreaction.

Garleanu, Pedersen and Poteshman (2009) construct a theoretical model which shows how option demand affects its price and skew as well as price and skew of other options written on the same underlying asset. The premise is that market-makers are unable to hedge a proportion of the risk faced when writing options with the result being that this risk is priced. It follows that an increase in net demand for options will be reflected in option price. Garleanu *et al* employ a unique data set which contains trading information on S&P500 and individual stock options. This data set allows them to analyse the net demand of public customers and firm proprietary traders from the start of 1996 through to the end of 2001. Net demand is computed as the sum of long open interest minus the sum of short open interest for each investor category. They find that index options are 'expensive' relative to individual equity options because of high positive demand by end-users. The higher is the demand from end-users then the higher the price of options. The effect is stronger following recent market-maker gains than following recent market-maker losses. Garleanu *et al* relate their empirical findings to their theoretical model, where the effect on price from an increase in demand is proportional to the component of the option that market-makers are unable to hedge. Hence Garleanu *et al* provide support for the demand-driven approach to option pricing although they do not identify any driver of demand from end-users.

Gettlemen, Julio and Risik (2011) build on the work of Amin, Coval and Seyhun, Bollen and Whaley and that of Garleanu, Pedersen and Poteshman by examining options written on individual stocks and constructing profitable trading strategies.

Gettleman *et al* identify significant stock price moves as the driver of option demand and perform short-term overreaction tests on individual stock options. They take it as given that demand is instrumental in option pricing and assert that it is possible to produce contrasting results to those of Bollen and Whaley by partitioning the stocks in a particular way. Rather than following previous studies by simply writing the most actively traded options, Gettlemen *et al* implement conditioning based on recent stock price performance. They examine the relationship between implied volatility of individual stock options in the S&P500 and the *ex post* realised volatility of those stocks following sharp movements in the underlying stock prices. Their key finding is that implied volatility is significantly higher than realised volatility. For example, following sharp stock price declines the implied volatility of short-term out-of-the-money puts is on average 31% higher than the realised volatility of the underlying stock over the remaining life of the option. Gettlemen *et al* are able to construct trading strategies, based on this finding, that systematically produce profits after allowing for transactions costs. This involves writing individual stock options following large stock price movements; a strategy which earns returns of up to 20% over a 30-day period.

Gettlemen *et al* point out that there is anecdotal evidence indicating that investors turn to the options market to act rapidly on pressing information. They argue that, as a consequence, there should be a systematic way to generate profits in the options market based on investor behaviour. If systematic profits can be generated then this represents a significant challenge to the weak form of the efficient markets hypothesis.

The finding of overpricing is interpreted as an indication of investor overreaction to recent information as opposed to the long term overreaction documented in the earlier literature. The overreaction is explained as a consequence of panic induced in unsophisticated investors by sharp price declines. These investors purchase out-of-the-money puts on stocks they own as insurance, causing implied volatility to rise to levels above the eventual realised volatility of the underlying stocks. In imperfect markets with limited arbitrage, sophisticated investors can sell out-of-the-money puts and delta hedge to earn significant profits.

The preceding literature in aggregate provides support for momentum effects and the presence of a demand parameter in option pricing. Trading strategies have been constructed to yield abnormal profits, but only conditional on sharp movements in the price of the underlying asset over a short time period. Writing options unconditionally does not appear to yield abnormal profits. The availability of consistent abnormal profits offers a challenge to the efficient markets hypothesis although limited arbitrage plays an important role.

2.7 Irrational Early Exercise of American-Style Call Options

Any finding of persistent irrational behaviour of investors is problematic for neoclassical finance as it clearly violates a key pillar. Any evidence of irrational behaviour in options markets, that supports that found in equity markets, provides further ammunition to the critics of efficient markets and supporters of behavioural finance.

According to Hull (2009), in the absence of market frictions, it should never be optimal to early-exercise an American-style call option written on a non-dividend-paying stock. This is simply because no interest income is sacrificed, the present value of the exercise price will fall as the option nears expiry and the option may yet go further into the money. Even if the investor perceives an opportunity to benefit from an overpriced stock it will be better to sell the option because its intrinsic value, $(S_t - K)$, will be less than the option's re-sale value. Poteshman and Serbin (2003) add that it is irrational to early-exercise American-style call options on dividend-paying stocks except for a period just prior to the ex-dividend date.

Finucane (1997) examines call options traded on the CBOE between 1988 and 1989 for irrational early exercise. He finds that around 20% of call exercise occurs at dates other than the ex-dividend date. Transaction costs lead to some early exercise being classified as rational when the difference between the exercise value and the value of the option is small. However approximately 40% of the contracts which are early exercised are done so irrationally where the cash flows received from exercising the option would have been less than those received from selling it. This finding roughly accords with that of Diz and Finucane (1993) who produce evidence of irrational early exercise in the S&P 100 index options market. The slight differences are attributed to the greater importance of dividends in stock options and greater importance of transactions costs in index options. Transactions costs may lead to rational early exercise of options particularly if the costs involved in selling an option are greater than those involved in exercising it. For example, Diz and Finucane note that the holder of an American-style index option may rationally early exercise to avoid the indirect costs of the index option bid-ask spread. The sale of the option will be at the bid price which may be below the exercise value of an in-the-money option. Dawson (1996) points out the institutional differences between the US and UK markets and presents evidence to demonstrate that the scale of transactions costs make it rational to sell or close out options rather than early exercise. An important exception is where investors wish to use their options to rebalance their portfolios of the underlying asset.

Early exercise may also be rational if there is a significant impact on the market for the underlying asset. If early exercise the asset price by a sufficient amount then early exercise could be worthwhile.

Poteshman and Serbin (2003) look for evidence of irrational behaviour of different categories of investor who exercise options early. They select a sample of all options listed on the CBOE and cover the period from 1996 to 1999. The sample is subdivided according to the assumed sophistication of each of three categories of investor. An irrational exercise is defined as one which violates non-satiation when allowing for commission and taxation effects. Evidence of irrational behaviour is usually challenged on the basis that investor rationality is normally assessed against an equilibrium model which may be misspecified. Poteshman and Serbin's tests are independent of any pricing model as the key to irrational investor behaviour is the comparison between cash flows from exercising or selling the option. Irrational early exercise is identified amongst customers of discount brokers and of full-service brokers but not amongst traders at large investment houses who trade for their firms' own accounts. Furthermore irrational early exercise is associated with underlying stocks reaching their highest levels over the past year and following periods of high underlying stock returns. This finding appears to be broadly consistent with the predictions of prospect theory as investors become more risk-averse relevant to a reference point following a gain.

More recent contributions to the literature focus on failure to early-exercise options when it is rational to do so. For example, Pool, Stoll and Whaley (2008), find that the failure to exercise call options prior to the ex-dividend date cost US option holders in the region of $491 million between January 1996 and September 2008. Furthermore, Barraclough and Whaley (2012) find that the failure to exercise put options cost US option holders in the region of $1.9 billion in foregone interest income over the same time period.

2.8 Trading Behaviour of Options Market Participants

Lakonishok, Lee and Poteshman (2003) associate behavioural finance with the activity of options market traders in terms of trading volume and open interest. They discover direct evidence of behavioural considerations. More precisely, Lakonishok *et al* analyse the behaviour of options market investors by attempting to address a number of questions. They employ detailed daily data on open interest and volume for all options listed on the CBOE from 1990 through 2001. This data is subdivided to reflect investors with varying degrees of sophistication. Open interest data provide long and short positions for each investor type. Volume data are classified by buying or selling investor and whether new positions are established or existing ones closed. The authors assert that this is a unique dataset.

The key objective of Lakonishok *et al* is to evaluate the extent to which behavioural factors, in particular the desire of investors to avoid regret, drive the use of options by investors with different degrees of sophistication. In particular, behaviour prior to and during the stock market bubble of the late 1990s and early 2000 is investigated.

Lakonishok *et al* create four volume categories and regress each of these on the underlying stock returns over various past horizons, underlying stock book-to-market ratios and underlying stock volatilities. The tests are used to investigate the factors that motivate option market activity and the extent to which different types of investor are momentum or contrarian. They also test the impact on option volume of shocks to the independent variables. The analysis is conducted over the entire sample period (1990-2001) and sub-periods to isolate the late ‘90s bubble. Options are also divided according to whether they are written on growth or value stocks and are tested for evidence of any change in investor behaviour after the bubble began to burst. Lakonishok *et al* produce a number of key findings which summarise the behaviour of participants in options markets.

The trading behaviour of participants in options markets suggests that they are loss-averse investors who engage in narrow framing. These investors are motivated by the need for satisfaction about their financial decisions as a result of avoiding outcomes that they subsequently regret.

Non-market maker investors are found to have short call option open interest positions that are larger than their long call option open interest positions. The short positions are held for considerably longer than the long positions. This finding suggests that calls are primarily used for hedging long stock positions rather than for speculating that stock price will fall. This finding is counter to the prediction of Lakonishok *et al* but may be consistent with loss aversion and narrow framing. They posit that positions in covered calls are being used to protect against losses in individual positions rather than as a leveraged position in a stock. Investors are also found to open more new short call positions following periods of high returns on the underlying asset. This effect was found to be particularly strong for wealthier investors. It is again argued that this is consistent with loss aversion and narrow framing whilst being exacerbated by the house money effect.

Non-market maker investors are found to have more open interest in short put than in long put positions. The rationale for option market traders to often sell out-of-the-money puts on perceived overvalued stocks is that if the stock price rises, or only declines slightly, during the option life the trader benefits by keeping the premium. If the stock price falls they believe that they are buying an undervalued stock at a very attractive price. This suggests that investors frame narrowly and focus on individual positions rather than their portfolios. Thus strategies emphasise reducing losses while heavily discounting gains.

Lakonishok *et al* find that non-market maker investors buy more calls to open new positions when past returns on the underlying asset are relatively high thus indicating trend chasing behaviour. This is observed for returns as far in the past as two years which suggests that investor sentiment is established over long horizons. It is also noted that writing more calls to open new short positions is positively related to past returns on the underlying stock. The short call position may be combined with a long stock to establish a conservative stock ownership position. The quantity of put options written to open new short positions is found to be negatively related to past returns on the underlying asset over the past quarter. Writing puts on stocks whose prices have fallen is found to become more attractive which is consistent with contrarian strategies.

During the late 1990s/2000 bubble the volume of call options purchased to open new positions by the least sophisticated investors was found to be much higher during the height of the bubble period as opposed to before or after. No similar pattern was observed when the behaviour of more sophisticated investors was analysed. Lakonishok *et al* argue that speculation from less sophisticated investors exacerbated the bubble although there was much less aggressive trend-chasing from more sophisticated investors. The absence of an increase in open buy put volume indicated that investors did not use the options market as a vehicle to overcome short sale constraints. In aggregate the buying and selling activity during this period indicates that, despite appropriate securities being readily available, investors find it difficult to trade against a bubble.

In summary the findings of Lakonishok *et al* are consistent with key behavioural finance concepts such as loss aversion, mental accounting/ narrow framing and regret avoidance. Surprisingly put options don't appear to be used as a means to overcome short sales restrictions. This may be partly explained by analyst focus on buy relative to sell recommendations.

2.9 Conclusion

The evidence reviewed above identifies behavioural biases that permeate the options market in a similar way to the stock market. Irrationality, overreaction, momentum, conservatism, representativeness and regret have all been highlighted in this chapter. It follows that analysis of the options market from a behavioural perspective is warranted. Evidence from the equity market combined with that from the options market provides ample justification for the analysis of relative option pricing, implied volatility, trading behaviour and momentum effects which form the basis of the next four chapters.

Chapter 3

Premiums on Stock Index Options and Expectations of the Early 21st Century Bear Market: Evidence from FTSE100 European Style Index Options

3.1 Introduction, Motivation and Literature

The central objective of this chapter is to test whether the relative prices and implied volatilities of traded put and call index options written on the UK large capitalisation index, the FTSE100, contain any predictive power for future stock market returns. If predictive power is contained in option prices and/or implied volatility then this may be used by options market investors to construct trading strategies that yield consistent abnormal profits where arbitrage is limited. The study is focused on the period preceding, and during the dot com bubble around the start of the 21st century.

Chen, Hong and Stein (2001) assert that the implied volatilities of stock index options have been strong indicators of negative returns in the U.S. stock market since the October 1987 crash. In addition, Rubinstein (1994) demonstrates that, since the 1987 crash, S&P500 options display a persistent implied volatility smile and implied volatility term structure. Simply put, as well as implied volatility being a function of strike price it also seems to be a function of the time remaining until the option matures resulting in a three-dimensional volatility surface. It is highlighted that similar, but not as pronounced, implied volatility surfaces are likely to be generated by options on other underlying assets including individual equity options. However, smiles for individual equity options are much flatter than those for index options. According to Toft and Prucyk (1997), the volatility smiles of individual equity options have been considerably flatter than those of index options since the 1987 stock market crash. Flatter volatility smiles make pricing of options more accurate when using standard option pricing models with lognormal distributions such as that of Black and Scholes (1973).

A higher volatility, implied by an option pricing model such as that of Black and Scholes (1973), is consistent with a higher option premium. As volatility is the key parameter in option pricing models that is not directly observable, implied volatility may be interpreted as picking up factors excluded from the model such as investor expectations. Clearly the volatility of an underlying security, such as a stock index, does not vary according to the strike price of an option. Hence, pricing options according to a volatility smile or smirk may be interpreted as either evidence of the presence of the influence of investor sentiment or a skewed risk-neutral distribution.

A key determinant of the option premium is the price of the underlying security. In particular, as prices fall put options become more valuable as there is an increased probability that the option will be in-the-money and by a greater amount. Similarly there will be an increased probability that call options will be out-of-the-money and will thus expire unexercised. It follows that bearish expectations of investors should be observable in puts having higher prices and greater implied volatility than corresponding calls. In addition concerns over the possibility of extreme market moves should be reflected in risk-averse investors pricing further out-of-the-money options by using higher implied volatilities. Bates (1991) focuses on whether or not out-of-the-money put options are *unusually* expensive relative to similarly out-of-the-money calls. Although there is no apparent solution to quantifying what is a *usual* premium, the relatively high price of stock index puts may be interpreted in terms of their portfolio insurance benefit. Demand is likely to be higher for puts to reflect the protection they offer against falls in portfolio value. There is unlikely to be similar demand for calls in terms of short stock portfolios, although calls do offer a relatively low risk long equity position.

Bates hypothesises that the U.S. market crashed in October 1987 because it was expected to crash. That is, the crash was a 'rational bubble'. If there is a rational bubble in stock prices then the price is made up of fundamental value plus an additional component. This reflects a self-confirming belief that the price depends upon a variable or variables that are intrinsically irrelevant. Bates argues that explanations that had previously been offered were not major enough to rationalise the magnitude of the crash. *Ex post* analysis would suggest that the market behaved in accordance with a rational bubble. However, after the event it is somewhat unsatisfactory to draw such conclusions from historical stock price movements due to hindsight bias. Greater inference could be drawn from some reliable indicators of crash expectations that could have been identified prior to the event. Bates interprets conditional skewness, inferred from options prices, as a measure of crash expectations. He finds that there was a strong perception of downside risk on the market during the year prior to the 1987 crash. This is evidenced by out-of-the-money puts being priced higher than out-of-the-money calls between October 1986 and August 1987. Implicit crash fears subsided as the market peaked in August 1987 and the relationship returned to 'normal' levels for the two months preceding the crash. Bates interprets this finding as an indication that, if the crash was a rational bubble, it burst in the month of August 1987 rather than in the subsequent October. This interpretation is not particularly convincing or well-argued. S&P500 futures options were still being written on the days leading up to the crash and it seems implausible that 'crash insurance' would become cheaper during this period. Furthermore, no compelling case is made as to why there would be a two month disconnect between events in the options and equity markets. Bates also finds that there was a resurgence in implicit crash fears after the stock market crash actually occurred which is consistent with traders pricing in concerns about future crashes as a reaction to the events of October 1987.

Two methods were used to demonstrate the finding of a strong perception of downside risk. Firstly, out-the-money put options were examined and found to be unusually expensive relative to out-of-the-money calls, a result that cannot be explained by standard option pricing models based on the assumption of positively skewed distributions. Secondly, a jump-diffusion model was fitted to daily options prices during 1987, and expected negative jumps were invariably found starting a year prior to the crash. Bates hypothesises that market participants expected substantial negative jumps, or crashes in the market during the year preceding the crash. He derives an option-pricing model for American style options on jump-diffusion processes, when jump risk is undiversifiable, under the hypothesis of time-separable power utility. The parameters of the risk-neutral process implicit in S&P 500 futures puts and calls' transaction prices are estimated using non-linear least squares. Bates estimates these implicit parameters for each day from 1985-1987 to produce a chronology of overlapping crash expectations:

- The volatility conditional on no jumps
- The probability of a jump
- The mean jump size (positive or negative) conditional on a jump occurring
- The standard deviation of jump sizes conditional on a jump occurring

Bates employs observations of transactions prices of S&P 500 futures options from 1985 – 1987. The objective is to identify any evidence of expectations of an impending stock market crash that can be inferred by option premiums. It is asserted that option prices give direct insights into the climate of expectations prior to the crash.

Bates points out that the major exchange traded index options in the United States are American style, which can be exercised at any time up until maturity. The possibility of early exercise can make it more difficult to isolate any indicator of crash expectations in put premiums. This difficulty arises because cash flows from the underlying index impart considerable influence on the optimality of early exercise. If the cost-of-carry parameter is significantly positive there is a greater likelihood of early exercise of American puts relative to calls and therefore they will have a higher premium. Similarly, if the cost-of-carry parameter is significantly negative then American calls are more prone to early exercise. To circumvent this problem Bates investigates options written on the S&P 500 futures contract and justifies this choice as follows:

"*In the special case of American options on futures contracts, however, the fact that the cost of carry is zero creates a knife-edge case in which the symmetry or asymmetry of the risk-neutral distribution is mirrored in the symmetry or asymmetry of the early-exercise decision for calls and puts and also in the early-exercise premia. For these options, relative prices of out-of-the-money calls and puts can be used as a quick diagnostic of the symmetry or skewness of the risk-neutral distribution, and thereby as a diagnostic of the merits of the underlying distributional hypothesis."*

Bates, D., 1991, pp 1014-1015

Bates refers to this diagnostic as a 'skewness premium'.

Gemmill and Saflekos (2000) propose a transformation of American to European style options, hence circumventing the early exercise problem. This involves using a binomial model, which considers dividends to compute an American style implied volatility. This implied volatility is then used to calculate the European option price with an equivalent binomial model.

Index options listed on LIFFE include European style contracts written on the FTSE100. Indeed, Brandt and Wu (2002) state that, during the time period relevant to this chapter, both European and American options with the same maturities are heavily traded 'side by side' on LIFFE.

Investigation into the behaviour of these put and call prices avoids the need to consider any early exercise option premium and should clearly indicate the presence of asymmetries suggestive of investor sentiment and, perhaps, crash expectations.

A further problem is that exercise prices set by LIFFE will be distributed asymmetrically around the underlying index value at any given point in time. Thus no consistent set of X% out-of-the-money puts relevant to X% out-of-the-money calls exists. To circumvent this problem interpolation must be performed between put and call data in order to produce comparable series.

The literature discussed in this chapter identifies the premiums and implied volatilities of 'out-of-the-money' options as indicators of crash expectations. The basic premise is that if investors expect stock prices to fall then the premiums of out-of-the-money puts will increase relative to those of similarly out-of-the-money calls. Bates (1991) examines the skewness premia on S&P 500 American style futures options and finds that this was indeed the case during the period prior to the crash of October 1987. Gemmill (1996) compares the markets of the United Kingdom and

United States. He finds no evidence to suggest that traders in London were overly concerned about the possibility of a crash either before or after the 1987 event. Chen, Hong and Stein (2001) note that in the United States, post-crash the implied volatilities of out-of-the-money puts have exceeded those for out-of-the-money calls; that is the volatility skew in index-implied volatilities is more pronounced in puts than in corresponding calls. One explanation of this feature of the smile is that traders are concerned about the possibility of a crash and that they price options according to these concerns.

If a significant relationship can also be identified between realised option premiums and subsequent stock market moves in more recent periods, then one could infer predictability in market prices. This would in turn appear to be a violation of weak-form market efficiency. Analysts would be able to recognise these patterns in security prices and may have the opportunity to trade accordingly. Even if no predictability can be inferred it may still be the case that option premiums and implied volatilities can provide interesting insights into investor sentiment.

If the premiums of out-of-the-money stock index put options can be demonstrated to be useful in forecasting extreme market movements, and these crashes can be attributed to behavioural causes, then not only is it apparent that behavioural influences are impacting on the underlying market variable, they are also playing a role in the pricing of the derivative security written on that index. Of particular concern is whether reliable indicators, such as option premiums, can demonstrate that crashes occur because they are expected to do so. Such a conclusion is consistent with Bates (1991) who interprets the crash of October 1987 as a self-fulfilling prophecy.

Gemmill (1996) focuses his study on volatility smiles in FTSE100 index options. The key objective is to investigate how the skewness of the smile changes over time and whether this process either predicts market movements or reflects past market movements. Gemmill's main finding is that skewness in the United Kingdom was unrelated to the 1987 crash. The finding is apparently inconsistent with that of Bates (1991) who finds that, post-crash, traders increase their purchases of put options in order to insure themselves against further crashes. One explanation for this inconsistency, proposed by Gemmill, is that the trading volume in index options in the United Kingdom was considerably less than in the United States hence there is insufficient liquidity in the former to facilitate portfolio insurance strategies by fund managers. Gemmill is inconclusive as to what drives the changes in volatility smiles over time although the implication is that a satisfactory behavioural theory is needed. Gemmill and Saflekos (2000) produce results that suggest that investor sentiment does affect the shape of implied distributions. However, this occurs after, rather than before, extreme market events. Hence, implied volatilities extracted from option prices will reveal investor sentiment but will have little, if any forecasting ability. Gemmill and Saflekos employ data taken from LIFFE over the period 1987-1997 to analyse a number of key sub-periods. In addition to the period around the time of the 1987 crash they look at the 1992 European monetary crisis, the 1997 Asian crash and the 1987, 1992 and 1997 British general elections. Similar results are found from analysing each of these periods, in that the options market is unable to predict crashes or outcomes, rather it reacts to them. However, they do conclude that implied distributions reveal market sentiment and may be useful to contrarian investors who do not agree with the consensus shape of the distribution.

An interesting extension to the work of Bates, Gemmill, Gemmill and Saflekos, and Chen, Hong and Stein involves investigating the ability of the premiums of out-of-the-money European style stock index options to forecast the relatively recent UK bear market. Such a study involves investigating realised values and implied volatilities of put and call options written on U.K. stock indexes for a period beginning four months prior to the bear market at the beginning of the 21st century and continuing up to 30th June 2002. This sub-period will be studied in order to determine whether there is any change in the forecasting ability of put option premiums and of the skew in index-implied volatilities. Indeed it will be argued that a bear market is suggestive of a period of consensus where investors share a common bearish belief. Hence arbitrageurs will be confident that common information signals will significantly reduce the possibility of information being concealed from the market. A further extension to the studies of Bates and Gemmill is to break the analysis down into a number of shorter sample periods. Consequently it will be possible to track the behaviour of skewness in option prices and implied volatilities over time.

For comparison, and as a test of the robustness of the results, the same procedures will be carried out on data relating to out-of-the-money put and call index options for the 1998-99 period. This sample period is selected in order to test for observable relationships when the market is in the midst of a period of sustained growth. For consistency, a period of sustained growth will be defined as one whose duration is at least as long as that of the bear market under investigation. Thus the aggregate stock market, proxied by the index underlying the options contracts, must have been rising for a period of two years prior to the sample. In this case we will be considering a period of options expiry from September 1998 to June 1999. This follows from, and is itself, a phase of sustained growth. For example, the FTSE100 on the 30th August 1996 stood at 3867 and had grown steadily to a level of 5249 by 31st August 1998.

3.2 Hypothesis and Methodology

The key hypothesis to be tested is that the premiums or implied volatilities of FTSE100 stock index options can be used to forecast subsequent movements in the underlying index. If this is the case, and traders price options according to their expectations, then this would suggest predictability in the aggregate stock market. The main focus of the analysis is on the period immediately prior to, and during, the recent bear market. This period, featuring the technology stock bubble, culminates in the most pronounced stock market fall since the 1987 crash.

Although the principal focus of this study is to examine the ability of out-of-the-money European style stock index options written on the FTSE100 to forecast the recent UK bear market, an earlier period is also analysed for completeness. The benefit of analysing this period, defined above, is that it will enable comparison between investor sentiment across different market conditions and potentially indicate if any observed predictability is bi-directional.

Initial testing will be focused on analysing the relative prices of out-of-the-money call and put options written on the FTSE100 up to and during the recent bear market. This will be followed by the estimation of Black-Scholes prices and implied volatilities for the contracts under consideration in order to construct and evaluate the resultant volatility smile or smirk. For comparison, data taken from a period of significant market growth will also be analysed. If call/put premiums are found to be less negative, neutral or positive during this period then weight will be added to the case for the predictive power of stock index options.

3.2.1 Call/Put Premiums

For each period of the analysis, premiums are used for put options with four different strike prices relative to the closing forward price for the underlying index, on each day. A higher subscript indicates the option is further out-of-the-money with the relevant strike price denoted $Kp_1, \ldots, Kp_4$, and the associated premium $p_1, \ldots, p_4$. To permit sensible comparison of put and call prices it is first necessary to create a synthetic call strike price $(Ksc_1, \ldots Ksc_4)$ in order to create a synthetic call premium $(sc_1, \ldots sc_4)$.[16] Rather than computing two series of options with constant moneyness, this study uses actual put prices as the base hence creating series which are themselves volatile. This approach requires only one artificial series to be created and provides a realistic representation of option price behaviour.

For example,

$$Ksc_{1i} = FTSE_i + (FTSE_i - Kp_{1i}) \qquad (3.1)$$

$$sc_{1i} = [(Ksc_{1i} - Kcb_i)/(Kca_i - Kcb_i)]x(ca_i - cb_i)+cb_i \qquad (3.2)$$

where:

Ksc_{1i} = synthetic call strike on day i

$FTSE_i$ = closing forward price on day i

Kp_{1i} = actual put strike on day i

sc_{1i} = synthetic call price on day i

Kcb_i = actual call strike below the forward on day i

Kca_i = actual call strike above the forward on day i

ca_i = actual call premium corresponding to Kca_i

cb_i = actual call premium corresponding to Kcb_i

[16] The computation of synthetic call prices needed to produce skewness premiums follows the procedure set out in Hull (2009) and equation (1) in Gemmill (1996).

Finally, a call/put premium is calculated which measures the price of an out-of-the-money call relative to that of a similarly out-of-the-money put. Or, the percentage deviation of x% out-of-the-money call prices from x% out-of-the-money put prices.

$$CP = (sc_{1i} – p_{1i})/p_{1i} \qquad (3.3)$$

Where,

p_{1i} = actual put premium relevant to Kp_{1i}

This statistic follows Bates' (1997) definition as a measure of moneyness bias known as a skewness premium. In other words equation (3.3) indicates the percentage deviation between call option and put option prices where, for each pair, the options are comparably out-of-the-money.

Call/put premiums were calculated for the range of out-of-the-money options for each of the thirty days in the sample period. Options with strike prices further out-of-the-money were not analysed as the volume of trading in these contracts was deemed insufficient to produce reliable prices and hence results.

3.2.2 Black-Scholes Prices

3.2.2.1 The Model

The starting point is the estimate of the theoretical Black-Scholes price for each out-of-the-money put option and corresponding synthetic call option. This may then be compared with actual premiums and used in the computation of implied volatilities. Prior to performing estimations using the Black-Scholes model it is important to consider the model of price behaviour that the underlying asset is assumed to follow. Bachelier (1900) proposed a model of the behaviour of stock prices that assumed that the underlying asset prices follow an arithmetic Brownian motion or generalized Wiener process.

$$dx = \mu dt + \sigma dz$$
$$where \qquad (3.4)$$
$$dz = \varepsilon\sqrt{dt}$$

The arithmetic Brownian motion contains a drift component and a volatility component, which includes the Wiener process *dz*. However, two problems arise in that an arithmetic Brownian motion permits asset prices to become negative and that expected return is not a function of asset price. Clearly, because of the property of limited liability, asset prices cannot become negative. For example, share prices, even when corporations go bankrupt, become worthless (i.e. zero price) and the shareholders' loss is limited to their investment.

Samulelson (1965), proposed an alternative stochastic process that overcomes these issues:

$$dx = \mu x dt + \sigma x dz$$
$$(3.5)$$
$$\frac{dx}{x} = \mu dt + \sigma dz$$

The process presented in equation (3.5) is known as a geometric Brownian motion. The important distinction between this process and the arithmetic Brownian motion is the inclusion of x. In the case of a share of stock x would be the stock price. A geometric Brownian motion is also a continuous-time Markov stochastic process and belongs to the family of Itô processes. It has the desirable property that x will always be non-negative provided that x_0 is non-negative. A continuous-time Markov stochastic process describes a variable that can change in an uncertain way at any point in time. The Markov property implies that only the current value of the variable is of any relevance in predicting the next value. This is clearly consistent with the weak-form of the efficient markets hypothesis. An Itô process refers to any generalized Wiener process with drift and volatility terms that can be functions of the underlying variable *x* and time *t*.

The price of any derivative is a function of the stochastic variables underlying the derivative, in this case the stock price and time. An important rule for the analysis of derivatives is Itô's Lemma. It is a partial differentiation rule that provides insights into the behaviour of functions of stochastic variables. It is clear that Itô's Lemma can be applied to the option pricing problem faced by Black, Scholes and Merton. This application, along with the concept of a no-arbitrage portfolio, is central to the following derivation, which is adapted from Hull (2009).

If we have a variable x that follows an Itô process

$$dx = a(x,t)dt + b(x,t)dz \tag{3.6}$$

Where dz is a Wiener process and *a* and *b* are functions of *x* and *t*. The variable *x* has a drift rate of *a* and a variance rate of b^2. Itô's Lemma shows that a function *G* of *x* and *t* follows the process

$$dG = \left(\frac{\partial G}{\partial x} a + \frac{\partial G}{\partial t} + \frac{1}{2} \frac{\partial^2 G}{\partial x^2} b^2 \right) dt + \frac{\partial G}{\partial x} b dz \tag{3.7}$$

Where *dz* is the same Wiener process as in equation (3.6). Thus, *G* also follows an Itô process. It has a drift rate of

$$\frac{\partial G}{\partial x} a + \frac{\partial G}{\partial t} + \frac{1}{2} \frac{\partial^2 G}{\partial x^2} b^2$$

and a variance rate of

$$\left(\frac{\partial G}{\partial x}\right)^2 b^2$$

The stock price is assumed to follow the geometric Brownian motion in equation (3.8).

$$dS = \mu S dt + \sigma S dz \tag{3.8}$$

μ and *σ* are constant. As discussed above, equation (3.8) is assumed to be a reasonable model of stock price movements. Itô's Lemma may then be applied, with the result that the process followed by a function *G* of *S* and *t* is

$$dG = \left(\frac{\partial G}{\partial S}\mu S + \frac{\partial G}{\partial t} + \frac{1}{2}\frac{\partial^2 G}{\partial S^2}\sigma^2 S^2\right)dt + \frac{\partial G}{\partial S}\sigma S dz \tag{3.9}$$

Both the stock price *S* and *G = f(S)* are affected by the same underlying source of uncertainty, the Weiner process *dz*. This property is of key importance to the derivation of the Black-Scholes model.

Equation (3.8) implies that asset prices are lognormally distributed, or alternatively that asset price returns are normally distributed.

$$\frac{\Delta x}{x} \sim N(\mu \Delta t, \sigma \sqrt{\Delta t}) \tag{3.10}$$

Black and Scholes used the process in (3.8) to model share prices in their option pricing formula. Since their work, a geometric Brownian motion is the usual assumption for asset prices in finance.

The Black-Scholes derivation considers the following 'no-arbitrage' portfolio of shares of stock and European call options written on that stock.

-1 call option, c

(3.11)

$\Delta \equiv +\frac{\partial c}{\partial S}$ shares, S

Π is defined as the value of this portfolio so that:

$$\Pi = -c + \frac{\partial c}{\partial S} S \tag{3.12}$$

$$d\Pi = -dc + \frac{\partial c}{\partial S} dS \tag{3.13}$$

and

$$\begin{aligned} d\Pi &= -\frac{\partial c}{\partial S}\mu S dt - \frac{\partial c}{\partial t} dt - \frac{1}{2}\frac{\partial^2 c}{\partial S^2}\sigma^2 S^2 dt - \frac{\partial c}{\partial S}\sigma S dz + \frac{\partial c}{\partial S}\left(\mu S dt + \sigma S dz\right) \\ &= \left(-\frac{\partial c}{\partial t} - \frac{1}{2}\frac{\partial^2 c}{\partial S^2}\sigma^2 S^2\right) dt \end{aligned}$$

(3.14)

The change in the portfolio value over an instant of time, *dt* is riskless. This is because it does not involve the Weiner process *dz*. To exclude the possibility of riskless arbitrage, the portfolio must instantaneously earn the same rate of return as other short-term risk-free securities. Thus

$$d\Pi = r\Pi dt \tag{3.15}$$

The result presented in equation (3.16) is achieved by substituting from equations (3.13) and (3.14).

$$\left(-\frac{\partial c}{\partial t}-\frac{1}{2}\frac{\partial^2 c}{\partial S^2}\sigma^2 S^2\right)dt = r\left(-c+\frac{\partial c}{\partial S}S\right)dt$$
$$-\frac{\partial c}{\partial t}-\frac{1}{2}\frac{\partial^2 c}{\partial S^2}\sigma^2 S^2 = -rc+\frac{\partial c}{\partial S}rS$$

$$\frac{1}{2}\sigma^2 S^2\frac{\partial^2 c}{\partial S^2}+rS\frac{\partial c}{\partial S}+\frac{\partial c}{\partial t}-rc=0 \qquad (3.16)$$

The final line of equation set (3.16) is known as the Black-Scholes partial differential equation. The particular solution for the European call is obtained by applying boundary conditions:

$$c(S,T)=(S_T-K)^+ \equiv \max(S_T-K,0) \qquad (3.17)$$

$$c(0,t)=0 \qquad \forall t\,\varepsilon[0,T]$$

The solution of (3.16) subject to (3.17) is the Black-Scholes formula for a European call.

$$c = S_0 N(d_1) - Ke^{-rT}N(d_2)$$

$$d_{1,2} = \frac{\ln(S/K)+\left(r\pm\sigma^2/2\right)T}{\sigma\sqrt{T}} \qquad (3.18)$$

$$N(x) = (2\pi)^{-1/2}\int_{-\infty}^{x} -e^{1/2s^2}\,ds$$

Where the function *N(x)* is the cumulative probability distribution function for a standardised normal distribution. Equivalently, the European put option is given by equation (3.19) with $d_1$and d_2 defined as in equation (3.18).

$$p = Ke^{-rT}N(-d_2) - S_0 N(-d_1) \qquad (3.19)$$

3.2.2.2 Risk-Neutral Valuation

The Black-Scholes partial differential equation and the resulting option price do not involve any variable affected by the risk preferences of investors. If risk preferences do not enter the equation, then clearly they cannot affect its solution. Thus, the very simple assumption that all investors are risk neutral can be made. So, in a risk-neutral world, the present value of any future cash flow can be obtained by discounting with the risk free rate. However the assumption of a lognormal risk-neutral distribution is likely to be inappropriate for the pricing of stock index options. For a European call, risk-neutral valuation implies that it can be assumed that the expected rate of return from the underlying asset is the risk-free rate of return. Then the expected payoff from the option at maturity can be calculated and discounted at the risk-free rate of interest.

Namely,

$$c = e^{-rT} E^{Q}\left[\max(S_T - K)^{+}\right] \tag{3.20}$$

Where $E^Q[x]$ denotes the expected value of x in a risk-neutral world. It can be shown that the expectation is equal to

$$E^{Q}\left[\max(S_T - K)^{+}\right] = S_0 e^{rT} N(d_1) - KN(d_2) \tag{3.21}$$

Substituting this in equation (3.20) results in the Black-Scholes equation.

$$c = S_0 N(d_1) - Ke^{-rT} N(d_2)$$

3.2.2.3 The Model Applied to FTSE100 Index Options

Theoretical prices of stock index options are normally calculated using the Black-Scholes-Merton model first proposed by Merton (1973), which allows pricing of European options on stock indexes with a known continuous dividend yield. Although dividend payments are made by firms at discrete intervals the assumption of a continuous dividend yield from a broad-based market index is commonly accepted and should not significantly bias the model's output. The option pricing formulae are as follows:

$$
\begin{aligned}
c &= S_0 e^{-qT} N(d_1) - K e^{-rT} N(d_2) \\
p &= K e^{-rT} N(-d_2) - S_0 e^{-qT} N(-d_1) \\
d_1 &= \frac{\ln(S_0 / K) + (r - q + \sigma^2 / 2)T}{\sigma\sqrt{T}} \\
d_2 &= \frac{\ln(S_0 / K) + (r - q - \sigma^2 / 2)T}{\sigma\sqrt{T}} \\
&= d_1 - \sigma\sqrt{T}
\end{aligned}
\tag{3.22}
$$

However, for the empirical analysis in this chapter Black-Scholes will be priced relative to the futures price as is common practice amongst traders. Using this approach accounts for the expected dividend yield on the spot position. The sample period analysed matches exactly that used when calculating synthetic call/put premiums. The time period, *T*, is given as the number of days remaining until the exercise date as a fraction of one year. A widely used proxy for the risk-free rate of interest is the return offered by three month Treasury Bills. UK three-month Treasury Bills are employed in this study.

Initially, consistent with Black and Scholes (1973), the volatility, σ, is estimated as the annual standard deviation of the underlying index and is updated daily by a moving average method. The estimation follows the procedure set out in Hull (2009). Hull recommends that although, *ceteris paribus*, more data generally result in greater accuracy, volatility does change over time and older data may have little relevance in predicting the future. It is suggested that a time window of 90-180 days is appropriate, with the number of observations, n, set to match the length of time remaining until the option matures. In the case of this study the options are relatively close to maturity and hence, for the purposes of computing each volatility estimate, n is set to 90 days. For example, the January 2000 contracts matured on 21st January. The volatility used to price these contracts on 1st November 1999 will be computed from returns on the FTSE100 for the 90 days prior to that date. Following Fama (1965) and French (1980) trading days will be used to estimate volatility. Thus annual volatility will be calculated as volatility per trading day multiplied by $\sqrt{252}$.

Volatility per trading day is computed in accordance with equations (3.23) and (3.24).

$$u_i = \ln\left(S_i / S_{i-1} \right) \qquad (3.23)$$

$$s = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n} u_i^2 - \frac{1}{n(n-1)}\left(\sum_{i=1}^{n} u_i\right)^2} \qquad (3.24)$$

One of the main problems with testing the Black-Scholes model has been the selection of an appropriate measure of volatility. As volatility is the only directly unobservable input into the Black-Scholes equation it is probable that many pricing errors occur as a result of incorrectly estimating the volatility of the underlying asset. An appropriate robustness test would be to estimate Black-Scholes prices using alternative volatility measures. Possible alternative volatility updating schemes that could be employed are the exponentially weighted moving average (EWMA) or the GARCH (1,1)[17].

The EWMA model presented in equation (3.25) is employed with a value of λ = 0.94. This is consistent with J.P. Morgan's RiskMetrics database. According to Hull (2009), J.P. Morgan's *RiskMetrics Monitor* (1995) asserts that a λ value of 0.94 gives estimates of volatility that provide the closest match to realised volatility.

$$\sigma_n^2 = \lambda\sigma_{n-1}^2 + (1-\lambda)u_{n-1}^2 \qquad (3.25)$$

Moving average daily volatilities are calculated using 252 daily observations and converted to annual volatilities.

The GARCH(1,1) model presented in equation (3.26) is employed for volatility updating using parameters produced by maximum likelihood estimation.

$$\sigma_n^2 = \omega + \alpha u_{n-1}^2 + \beta\sigma_{n-1}^2 \qquad (3.26)$$

where

$$\omega = \gamma V_L$$

Intuitively, using daily data a GARCH(1,1) models today's estimate of volatility squared as a weighted average of the long-run variance rate, yesterday's market return squared and yesterday's volatility forecast.

The GARCH(1,1) model may improve upon the EWMA as it gives some weight to the long-run average variance rate thus allowing for mean reversion as well as

[17] The GARCH estimation employed here is not to be confused with the GARCH option pricing models proposed by Duan (1995), Heston and Nandi (1999) or Ritchken and Trevor (1999). In this study EWMA and GARCH are merely being employed to forecast the volatility parameter for a Black-Scholes framework.

volatility clustering in the data. The parameters estimated, using daily index returns, over a one-year period are as follows:

$$\varpi = 0.000000591$$
$$\alpha = 0.048833$$
$$\beta = 0.944422$$

Although it is not the purpose of this study to test for the true measure of volatility for the FTSE100, the additional checks are necessary to investigate whether the results are robust against different measures of volatility.

Once Black-Scholes prices have been computed, using each estimate of the current values of volatility, they are compared with the observed market put prices and synthetic call prices. The mean of this difference is calculated as is its standard deviation.

More importantly, deviations of the Black-Scholes predictions from observed values across all estimated measures of volatility will act as justification for employing implied volatility. If significant deviations are observed, implied volatility must be picking up misspecifications in the Black-Scholes model as all other inputs are directly observable. Thus an analysis of implied volatility would be likely to produce more meaningful conclusions.

3.2.3 Implied Volatility

Implied volatility may be defined as the volatility of the underlying asset implied by an option pricing model using observed market option prices. It is important to calculate implied volatility because it represents the market’s view of the future volatility of stock returns. Increased volatility is generally associated with negative perceptions of the future movements in the aggregate stock market and is hence a useful indicator of crash expectations. It should be possible to construct a time series of implied volatility which is indicative of consensus among traders' estimates of changing volatility before and during the bear market at the turn of the century. Justification for the analysis of implied volatility is provided by Chiras and Manaster (1978). They employed data from the Chicago Board Options Exchange to compute implied volatility. The explanatory power of the implied volatility was then compared with that of historical volatility with the result that the former was found to provide much better estimates of future volatility. This suggests that traders have access to, and are using, more than simply historical data to form their expectations. Implied volatilities are based on current prices and would therefore be expected to have future expectations impounded in them. Gemmill (1996) argued that implied volatility is preferable to prices when calculating skewness for a number of reasons. Firstly, as option prices are almost linear in volatility there should be very little difference in the behaviour of an implied volatility-based and a price-based measure of skewness. Second, the volatility-based measure has the advantage that, unlike prices, volatility is not sensitive to maturity. Gemmill asserts that this should make the volatility-based measure less prone to sampling error. A further advantage is a consistency with market practice in that traders talk in terms of volatility as opposed to price smiles. Gemmill and Saflekos (2000) assert that traders price options using a Black-Scholes model but with different levels of volatility applied to each exercise price, resulting in a volatility smile. They would then apply the volatility smile from day t-1 to compute the prices of options on day t. This is clearly inconsistent with the theoretical model in which volatility is assumed to be constant across all exercise prices. In addition, MacBeth and Merville (1979) note that, for individual equities, implied volatilities are higher for in-the-money than for out-of-the-money contracts. This finding contradicts that of Black (1975) who finds the opposite result. Furthermore, Merton (1976) found implied volatilities that were high for both deep in- and out-of-the-money options. The one obvious conclusion to draw from these results is that there is variability in the market's expectation of the volatility of the underlying asset over time.

It is important to exercise caution by recognising some of the weaknesses in the predictive power of implied volatility. For example, Canina and Figlewski (1993) analysed the predictive power of implied volatility extracted from S&P 100 options. They examine returns on the S&P 100 index between 1983 and 1987 and discover that the implied volatility forecasts are biased. Furthermore Canina and Figlewski do not find statistically significant forecasting power. However Christensen and Prabhala (1998) adjust Canina and Figlewski's methodology and extend the sample period by 8 years to find implied volatility which is unbiased and has statistically significant forecasting power.

Once implied volatilities have been calculated they may then be displayed graphically as a volatility smile or skew. Further and more in-depth analysis of literature in this area will be presented in relation to implied volatility indexes in Chapter 4.

Implied volatility needs to be calculated using an iterative procedure such as that used by the solver add-in in Microsoft Excel. The package chooses alternative values of implied volatility so as to minimise

$$(\hat{c}-c)^2$$

where

$\hat{c} =$ theoretical (B-S) premium

$c =$ quoted call premium

The purpose of calculating implied volatilities of put and synthetic call options is to determine if the implied volatility of the former exceeds that of the latter. Also the intertemporal magnitude of this relationship is of interest, based on the assumption that there is a usual degree of skewness.

The Black-Scholes model gives rise to the expectation that implied volatility will be constant across puts and calls and also across exercise prices. In other words the volatility smile will be flat. The market view of the volatility of the underlying asset at a particular point should not change simply because a different class of derivative is being priced. However there may be an expectation of observing differing volatilities for puts and calls asymmetrically distributed around the spot price. Differing implied volatilities for different degrees of 'moneyness' within an option type is evidence of a symmetric or asymmetric volatility smile (or skew) which is not flat. Evidence of such a pattern of implied volatility suggests some type of inaccuracy in the Black-Scholes model. In particular, the Black-Scholes model is objective in that it does not provide for investor sentiment or the pricing of jump risk. However, the purpose of this study is not to test the validity of the pricing model, rather the intention is to identify evidence of traders' expectations and if those expectations are fulfilled. Further, volatility smiles and skews may correspond to negatively skewed implied probability distributions.

Implied volatilities for each contract are calculated for both put and synthetic call contracts and their development over time is studied. The relative implied volatilities can then be compared by calculating a percentage difference for each contract on each day. A mean value of percentage difference in implied volatility is then produced for each degree of 'moneyness' of a particular contract. A positive value indicates greater implied volatility in puts whereas a negative value indicates greater implied volatility in calls.

3.3 Data

Aggregate end-of-day values for the FTSE100 index, FTSE100 futures price and rates of return on UK 3-month Treasury bills are collected from Datastream. These are consistent with data on the associated European style index options contract listed on the London International Financial Futures Exchange (LIFFE)[18]. Owing to the relatively low option trading volume during the period of analysis the options selected are those closest to maturity as these contracts account for the bulk of the trading volume. Options with a variety of maturities will be examined in Chapter 6 in relation to momentum and overreaction tests. The data employed in Chapter 6 is sampled over a more recent period and is associated with higher trading volume of FTSE100 index options. The average moneyness of each series of put call pairs is given in Table 3.0. Moneyness is defined as the exercise price divided by the forward price. These values are consistent with out-of-the-money puts. The moneyness of a call in a matched pair will be approximated by the reciprocal.

Table 3.0 Average Moneyness of Series of Option Pairs

Series Title	CP1	CP2	CP3	CP4
K/F	0.994448	0.986345	0.978242	0.970139

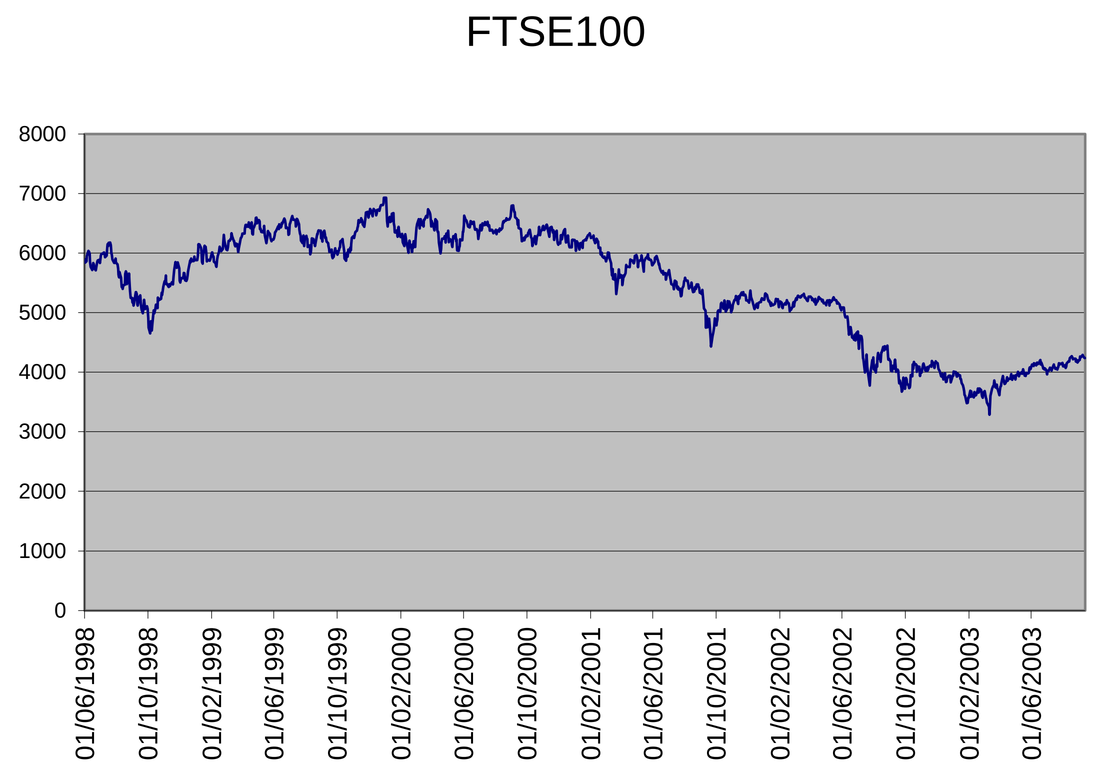
[18] Options data is purchased from LIFFE Euronext Online. The options selected expire on the third Friday of the delivery month or the preceding Thursday if the Friday is a public holiday.

Although some studies employ the LIBOR as the risk free rate for option pricing the selection of rate is of little importance due to the relative insensitivity of option price to this parameter as asserted by Macbeth and Merville (1979). Furthermore, Black (1989) has noted that, in general, it is volatility rather than interest rates that has the most significant impact on option prices.

The data collected begin from 1^{st} June 1998 continuing up to, and including 30^{th} June 2002. This allows examination of the period prior to and during the recent bear market and allows comparison of expectations across a range of different time periods.

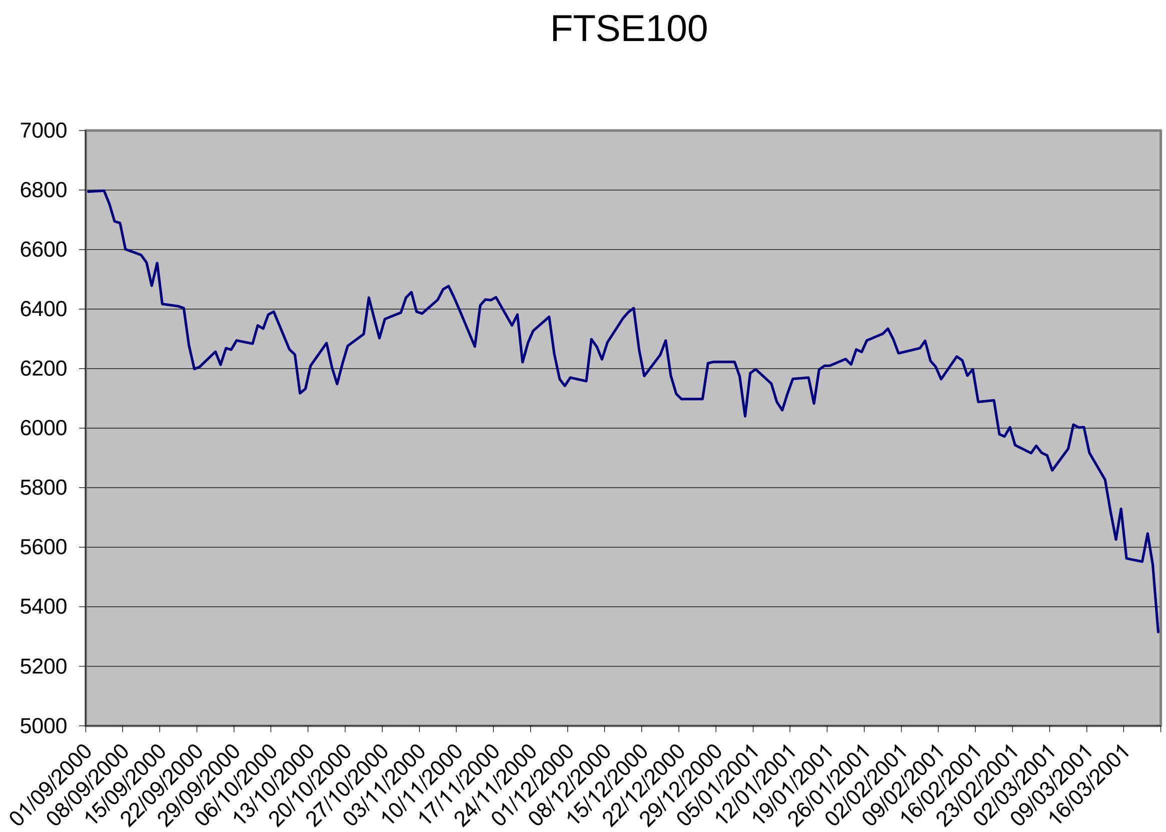
Figure 3.1 illustrates the level of the index underlying the options contracts over the period 1^{st} June 1998 to 12^{th} September 2003. It can be clearly observed that the FTSE100 index peaked at the beginning of January 2000. However, it must be noted that the downturn was initially gradual with some sustained periods of stability. One would expect that there would be little initial impact upon investor expectations simply because there is only a very small change over the first twelve months. This may be regarded as short-run fluctuations which would not appear to be indicative of a long-run trend. However, from the beginning of 2001 the downturn gains momentum and, if traders are already bearish, this should be more likely to have a significant impact on their expectations. Or more precisely, it should increase the likelihood of them implementing protective put strategies. This in itself would not necessarily indicate any inefficiency in the market, rather it would be consistent with traders adjusting their expectations in response to the arrival of new information. For any inefficiency to exist it needs to be shown that traders are able to identify a period of falling prices prior to those price falls occurring.

Figure 3.1 FTSE100 Stock Index 1/6/1998-12/9/2003



A plot of shorter sub-periods emphasises some of the more dramatic episodes of decline in the UK large capitalisation market following the burst of the dot com bubble. For example, Figure 3.2 charts the FTSE100 index level across the period from September 2000 to March 2001, during which there was a drop in the index of approximately 1400 index points.

Figure 3.2 FTSE100 Stock Index 1/9/2000-22/3/2001



Options on the FTSE100 expire in March, June, September and December plus such additional months that the nearest four months are available for trading. The last trading day for the options is the third Friday of the expiry month. Settlement is in cash, with the underlying contract being traded at £10 per full index point and a minimum price movement of 0.5 of a point. Contracts are available for exercise prices at 50-point intervals ranging in- and out-of-the-money relative to the current level of the FTSE100 index, plus the contracts opened previously. It follows that the range of contracts available for a given maturity will depend upon the past movements of the underlying market during the history of that maturity of option. European index options are heavily traded on LIFFE. For example, according to Fahlenbrach and Sandas (2003), in the first six months of 2001 the European style

FTSE 100 index option contract had an average monthly volume of 1.25 million contracts and an average monthly open interest of over 1.4 million contracts.

Initially tests were performed on closing put and call premiums from 1st November 1999 to 10th December 1999 for European style contracts due to expire in January 2000. This is the first contract to expire after the FTSE100 peaked on 3rd January 2000.

Consistent with Bates (1991), the sample excludes contracts with maturity in excess of 118 days and less than 28 days. Longer maturity contracts are too thinly traded and those of shorter maturity too close to expiration, and hence information may be obscured by the associated market activity, to provide reliable indicators of crash expectations. Moreover, Heston (1993) argues that very short term options have substantial time decay that could interfere with the ability to isolate the volatility parameters, and very long term options are simply not actively traded.

End of day prices at four strike prices for calls and four strike prices for puts are used in order to ensure a reasonably wide ‘moneyness’ range. Again, contracts further out-of-the-money are considered to be too thinly traded to provide reliable information. In the case of FTSE100 options, many contracts outside of the selected moneyness range are not traded at all during the sample period.

End-of-day data should be sufficiently frequent in order to analyse investor sentiment because, if crash expectations persist over a lengthy time period, it is unlikely that significant information will be revealed by the pattern on a single day other than perhaps the day prior to the onset of a crash. However the bear market that began in 2000 was gradual and the data is unlikely to exhibit anything as dramatic as the crash of 1987 for example.

As options are only available for specific exercise prices determined by the exchange, the exercise prices of out-of-the-money puts and calls will be asymmetrically distributed around the value of the underlying index. For example, on the 1st November 1999 the FTSE100 closed at 6284. On the same date there was also a call option with strike price 6325. That is, forty-one index points out-of-the-money. However there was no exchange-traded put option with a strike price of 6243. The nearest out-of-the-money contract to the spot price had a strike of 6275. Clearly this means that any comparison between put and call premiums will reflect not only crash expectations but also the differing degrees of 'moneyness.'

To address this problem an iterative interpolation process is employed in order to produce option prices distributed symmetrically around the index value. This process is used to adjust call prices to create what will be referred to as a 'synthetic call premium'. This follows the procedure adopted by Gemmill (1996) who uses linear interpolation to produce implied volatilities of options with strike prices 2% away from the forward price.

All options used are European style thus avoiding the problem of any early exercise premium associated with American options.

3.4 Results and Analysis

3.4.1 Call/Put Premiums

The results presented in Table 3.1 are based on the prices of options that expire on the third Friday of the delivery month. The expiry month for each contract is given in the first column of the table. Call/put premiums, or skewness measures, of out-of-the-money options with exercise prices evenly distributed around the forward price are presented. Synthetic call/put pairs are matched in terms of moneyness and maturity. The moneyness range, CP1 to CP4 is defined in Table 3.0. For consistency each monthly series is sampled at the end of each of the 30 trading days prior to the final 30 days of trading. Thus the sample period is T-60 to T-30, where T is the expiry date and only trading days are counted.

Table 3.1 Mean Synthetic Call/Put Skewness Measure

Contact Expiry January 2000 – June 2002

$$\boldsymbol{CP_i = (\widehat{c_i} - p_i)/p_i}$$

Expiry	*N*	*CP1*	*CP2*	*CP3*	*CP4*
January 2000	30	-0.038451***	-0.00519	-0.05342***	-0.11351***
		(4.413933)	(-0.61286)	(-5.87339)	(-11.2141)
March 2000	30	-0.09721***	-0.13214***	-0.17069***	-0.21374***
		(-10.6153)	(-14.2787)	(-17.4542)	(-21.4929)
June 2000	30	-0.11356***	-0.14355***	-0.17681***	-0.2195***
		(-8.74182)	(-10.9059)	(-13.2547)	(-15.5118)
September 2000	30	-0.10878***	-0.1393***	-0.17341***	-0.21328***
		(-8.1671)	(-10.1632)	(-11.8888)	(-13.4478)
December 2000	30	-0.1852***	-0.21749***	-0.25319***	-0.2933***
		(-26.0485)	(-29.1955)	(-31.3221)	(-32.5510)
March 2001	30	-0.2028***	-0.23882***	-0.27956***	-0.3247***
		(-69.552)	(-74.8194)	(-66.5500)	(-56.1617)

June 2001	30	-0.1736***	-0.20771***	-0.24731***	-0.2941***
		(-42.1105)	(-38.4579)	(-34.7471)	(-30.6061)
September 2001	30	-0.15357	-0.18787	-0.2287	-0.27675
		(-54.5713)***	(-57.5087)	(-57.2304)	(-52.9571)
June 2002	30	-0.11893***	-0.17351**	-0.2360***	-0.30522***
		(-11.6009)	(-16.4031)	(-20.7238)	(-23.2497)

Numbers in parentheses are t-statistics. *** significant at the 1% level, ** significant at the 5% level. Critical values are 2.462 and 2.045 respectively.

The results presented in Table 3.1 are all negative and, apart from the second out-of-the-money series maturing in January 2000, are all significant. This is consistent with a 'usual' situation of puts priced highly relative calls matched by moneyness and maturity. The most notable feature of the results is the shift in both the size and significance of the skewness measure that occurs between observations on the contracts maturing in September and December 2000. The FTSE100 fell by less than 0.5% in the period between the observation mid-points of the two series. However the index fell by 3.78% between the expiry dates of the respective option contracts. This finding is consistent with a strong perception of downside risk amongst option traders towards the end of 2000.

The smallest and least significant values of the skewness measure relate to values of the January maturity option pair from prices in November and December 1999. This may be interpreted as the highest level of trader optimism throughout the sample period. The value of the skewness measure increases consistently for the March, June and September maturity contracts prior to the major shift.

With regard to moneyness the expensiveness of puts relative to calls increases as options are observed further out-of-the-money. This provides support to the findings of Rubinstein (1994) and Chen, Hong and Stein (2001) that traders are concerned about the possibility of a downturn and weight this more highly than the possibility of an upturn. They then price put and call options to accord with these concerns.

The move from the January to the March contract also coincides with a shift in the size and significance of the synthetic call/put skewness measure. Although this shift is not of the magnitude of that observed later in the year it is noteworthy as it coincides with the onset of the downturn. Observations on this contract run through January up to the 14th of February 2000. Out-of-the-money put premiums have clearly increased, compared to observations on the preceding contract, relative to those of the corresponding out-of-the-money synthetic call premiums during this period. This result may be interpreted as traders becoming more pessimistic about future market moves. The large negative figure for the deepest out-of-the-money options suggests that traders believe that a large market downturn is considerably more likely than an upturn of similar magnitude. This pricing behaviour is consistent with aversion to extreme losses.

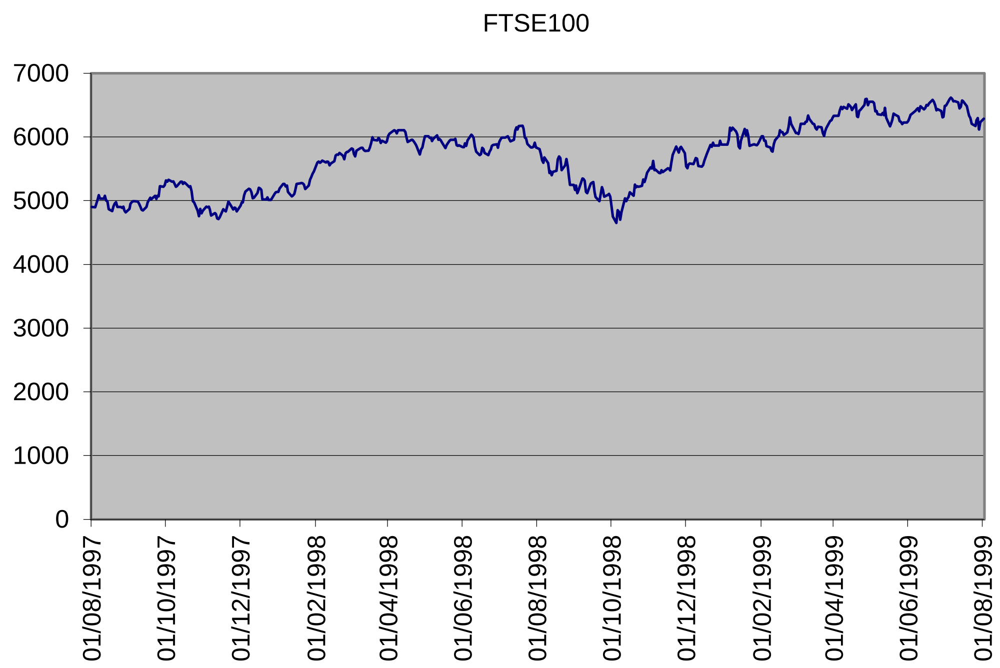
The results for the remainder of the period show a steady decline in the value of the skewness measure for options near the money. However, for the deepest out-of-the-money options the value of the skewness measure remains consistently high. As the prices of deepest out-of-the-money options hold the greatest amount of information (for example see Pan and Poteshman, 2006), they provide important insights into the expectations of investors. As all of these values are negative and significant, with a mean value of -0.2988 for the December 2000 through September 2001 contracts, it can be inferred that options investor expectations were bearish throughout this period.

A notable feature of Figure 3.1 is a data ‘spike’ and high level of market turbulence around the time of the events of September 2001. Option premiums could not be expected to contain any predictive power related to extreme events of this nature. It is decided therefore to exclude this period from the analysis as any results produced could not be sensibly interpreted as they are likely to be seriously biased. However the resilience of the market can also be observed in that it takes very little time for 'normal' conditions to return. In the light of this it would not seem unreasonable to continue the analysis by producing synthetic call/put premiums for the March 2002 contract with observations beginning in January of that year. During the observation period the FTSE100 fluctuated between 5124.5 and 5275 points. The mean value of the call/put premium is still negative and significant but with a larger divergence of that for deepest out-of-the-money options from that for closest out-of-the-money options. The value of -0.11893 for closest out-of-the-money options can be interpreted as the likelihood of exercise of calls and puts being relatively even. Whereas the value of -0.30522 for the deepest out-of-the-money options indicates that traders are becoming increasingly concerned about the possibility of a major market fall. Furthermore, the overall trend for deepest out-of-the-money options indicates that traders are becoming ever more pessimistic about the future direction of the aggregate stock market in the U.K. What the results certainly provide is a fascinating time line of shifting investor sentiment during the sample period.

The lower the index is expected to be, the higher should be out-of-the-money put prices relevant to equivalently out-of-the-money calls. Clearly the payoff to the holder of the put option at expiration will be $\max(K–S_T,0)$. As the contract is effectively a zero-sum game the maximum loss to the writer of the option is $–(K–S_T)$. Thus the lower the anticipated level of the index then the higher will be the price of the put relative to the call and hence the lower the value of the skewness premium. What traders are expressing is a view on what is the most likely level of the index on the date of the expiration of the option. A sample of volatility smiles are presented later in this chapter which provide an illustration of the evolution of investor sentiment across the crisis period.

A period of sustained growth has been selected in order to draw comparisons with the results presented in the previous section. Figure 3.3 illustrates the steady growth in the FTSE100 stock index in the second half on 1998 and throughout the first half of 1999. Identical tests to those performed on contracts in the bear market will be applied to the September and December 1998, and March and June 1999 expiration contracts. These are the calculation of synthetic call/put skewness premiums, Black-Scholes analysis and investigation of implied volatility. This period of steady growth as opposed to decline exhibits a similar degree of stock market volatility to that following the turn of the century.

Figure 3.3 FTSE100 Stock Index 1/8/1997-1/8/1999



Mean synthetic call/put skewness measures are presented in Table 3.2.

Table 3.2 Mean Synthetic Call/Put Skewness Measure

Contract Expiry September 1998 – June 1999

Expiry	*Observations*	*CP1*	*CP2*	*CP3*	*CP4*
September 1998	30	-0.2404	-0.27107	-0.30851	-0.35344
		(-44.8016)	(-45.7967)	(-51.8877)	(0.034334)
December 1998	30	-0.14712	-0.18131	-0.21899	-0.26135
		(-35.3770)	(-35.6990)	(-34.5475)	(-37.3776)
March 1999	30	-0.11203	-0.1396	-0.16929	-0.1994
		(-47.3799)	(-55.8871)	(-49.9947)	(-45.6029)
June 1999	30	-0.18781	-0.18781	-0.22816	-0.2723
		(-51.2229)	(-51.2229)	(-58.7345)	(-58.4907)

Figures in parentheses are t-statistics.

All of the skewness measures contained in Table 3.2 are negative and significant indicating that FTSE100 put options remain expensive relative to corresponding calls for each degree of moneyness.

The first row of observations contained in Table 3.2 relate to the period July 1st to August 11th 1998. During this period the FTSE100 fluctuated between 5435 and 6222 points. A notable feature of the results is that out-of-the-money puts are still expensive relative to out-of-the-money calls despite the general trend of the aggregate UK stock market in 1998 being upward. Furthermore, the relationship becomes more pronounced according to how far out-of-the-money the series is. This finding poses a number of questions:

(i) Do the data suggest that market participants are pessimistic at this point in time? This, in itself, would not be a violation of market efficiency.

(ii) Is there a detectable pattern in the relationship between put and call options and hence a violation of market efficiency? That is, if the relationship between equally out-of-the-money puts and calls consistently predicts aggregate market moves, such predictability contradicts the weak form of the efficient markets hypothesis.

(iii) Are investors becoming more optimistic but, perhaps because of anchoring and/ or conservatism, this optimism is subject to a lag? This would also contradict market efficiency.

(iv) Are the data merely demonstrating a persistent relationship between the relative premiums of out-of-the-money puts and calls? If this were the case then there would be no repeating patterns in prices that could be exploited by arbitrageurs. Hence, at most this would represent a technical inefficiency.

In an attempt to address these questions the results for the next three contracts under investigation are presented in the next three rows of Table 3.2.

The second row of observations relate to the period October 1st to November 11th 1998. During this period the FTSE100 fluctuated between 4699 and 5664 points. Although the aggregate market dipped during this period, as can be observed on Figure 3.2, the pattern of the mean call/put premium displayed in Table 3.2 is very similar to that for the September contract. Thus it is difficult to draw any further inferences. The third and fourth rows of observations relate to the period from January 4th to February 12th 1999 and April 1st to May14th 1999 respectively. During this period the FTSE100 fluctuated between 5765 and 6635 points. With reference to the questions posed earlier:

(i) Overall it would appear that traders remained concerned about the possibility of a market decline as puts are consistently expensive relative to calls.

(ii) It is not possible to confidently infer market predictability from these results.

(iii) It may be that traders are slowly becoming more optimistic, however it seems that pessimistic expectations persist within risk-averse traders alongside aversion to extreme losses.

3.4.2 Black-Scholes Prices

The Black-Scholes model, using the relevant futures contract as the underlying asset, is employed to price FTSE100 index options. The null hypothesis is that there will be no significant difference between the Black-Scholes price and the market price. The alternative hypothesis is that the Black-Scholes model will produce systematic and significantly different prices to those observed in the market. The model is estimated using standard deviation as the traditional measure of volatility. However, as a robustness check, volatility is also estimated using an EWMA and GARCH(1,1) model which allow for time varying volatility. Rejection of the null hypothesis motivates the analysis of implied volatility for further tests, as the volatility parameter will be picking up other influences, such as investor expectations, not included in the specification of the model.

The reported statistics are numbered by moneyness, M, which runs from 1 to 4 and have the same values as presented in table 3.0 corresponding to CP1 to CP4. Hence these denote, for each contract, the nearest to fourth nearest out-of-the-money options respectively. The mean statistic in column four, in each case, tells us the mean value, over the sample period for a particular contract, of the observed (or synthetic) option price minus the theoretical Black-Scholes price. If the value is positive then the Black-Scholes model is underpricing the option, and if negative the model is overpricing the option.

The Black-Scholes analysis generates some interesting results. The first notable feature is the divergence of the theoretical call price from the observed price. In order to verify that this finding was not simply attributable to the method used to calculate synthetic call premiums the same calculations were applied to actual out of the money call contracts. On average the percentage divergence of the actual call price from the Black-Scholes price was found to be at least as large as was found when using synthetic calls.

Table 3.3 Percentage Deviation of Theoretical Black-Scholes-Merton Price from Synthetic Call Premium and Actual Put Premium 2000

Maturity	M	Contract	Mean Pricing Error		
			Standard Deviation	EWMA	GARCH
Jan	1	Call	-0.10316*** (-10.7547)	-0.01038 (-1.27485)	-0.01606* (-2.09031)
		Put	0.251308*** (16.20808)	0.475771*** (26.28433)	0.459719*** (29.81945)
	2	Call	-0.12603*** (-11.9435)	-0.02122** (-2.30409)	-0.02783*** (-3.22064)
		Put	0.295601*** (17.05338)	0.572783*** (26.20732)	0.553062*** (29.83999)
	3	Call	-0.15154*** (-13.4329)	-0.03426*** (-3.46688)	-0.04186*** (-4.56952)
		Put	0.372214*** (19.49185)	0.694381*** (26.43539)	0.669971*** (30.3943)
	4	Call	-0.18195*** (-14.7245)	-0.05224*** (-4.67709)	-0.06089*** (-5.90646)
		Put	0.488826*** (23.18965)	0.842336*** (26.67895)	0.811952*** (31.02001)
Mar	1	Call	0.004494 (0.377577)	-0.06462*** (-2.30244)	-0.04329* (-1.74649)
		Put	0.884263*** (28.38101)	0.707325*** (6.054117)	0.759051*** (7.835681)
	2	Call	0.004294 (0.325414)	-0.07242** (-2.20215)	-0.049** (-1.69909)
		Put	1.039308*** (29.25237)	0.838331*** (5.701576)	0.895404*** (7.442147)
	3	Call	0.001931 (0.133739)	-0.08211** (-2.13396)	-0.05673** (-1.69503)
		Put	1.223234*** (29.53575)	0.997892*** (5.313873)	1.05945*** (6.989161)
	4	Call	0.001363 (0.084821)	-0.09013** (-2.01395)	-0.06287* (-1.62843)
		Put	1.452179*** (30.5598)	1.201166*** (4.964374)	1.265934*** (6.585095)
Jun	1	Call	-0.1712*** (-8.95433)	-0.17916*** (-8.86636)	-0.16614*** (-7.61992)
		Put	0.367675*** (9.318349)	0.347601*** (7.789321)	0.436964*** (8.839514)
	2	Call	-0.1885*** (-8.90713)	-0.19701*** (-8.78896)	-0.18195*** (-7.5991)
		Put	0.419902*** (9.388686)	0.397728*** (7.821245)	0.498969*** (8.911336)
	3	Call	-0.20739*** (-9.00197)	-0.21642*** (-8.84255)	-0.19924*** (7.67228)
		Put	0.484862*** (9.623212)	0.460472*** (7.958929)	0.575825*** (9.086265)
	4	Call	-0.2301*** (-9.09137)	-0.2396*** (-8.9133)	-0.22036*** (-7.77512)
		Put	0.562755*** (9.930322)	0.535744*** (8.15939)	0.667974*** (9.307021)
Sep	1	Call	-0.36441**	-0.23746***	-0.24496***

			(-48.8095)	(-38.8074)	(-45.4197)
		Put	0.175372*** (20.42252)	0.800301*** (15.19505)	0.744521*** (18.78662)
	2	**Call**	-0.39771*** (-45.5732)	-0.25444*** (-37.6116)	-0.26361*** (-44.5011)
		Put	0.184841*** (18.27696)	0.932832*** (14.09144)	0.860127*** (17.49945)
	3	**Call**	-0.4339*** (-44.3994)	-0.27429*** (-36.7682)	-0.2853*** (-44.1446)
		Put	0.199645*** (16.2697)	1.100709*** (12.94113)	1.005273*** (16.05732)
	4	**Call**	-0.46706*** (-43.9061)	-0.2883*** (-22.9661)	-0.30177*** (-28.2244)
		Put	0.222192*** (14.8082)	1.315972*** (12.03028)	1.189654*** (14.95187)
Dec	**1**	**Call**	-0.06144*** (-3.21202)	-0.03508* (-1.47214)	-0.02951 (-1.26421)
		Put	0.624373*** (13.13467)	0.81879*** (13.80338)	0.834038*** (14.95094)
	2	**Call**	-0.06627*** (-2.95612)	-0.03148 (-1.08143)	-0.02515 (-0.91865)
		Put	0.727549*** (13.34351)	0.967036*** (13.62529)	0.985076*** (14.86255)
	3	**Call**	-0.07564*** (-2.9793)	-0.0315 (-0.94349)	-0.02439 (-0.78272)
		Put	0.85732*** (13.36909)	1.154763*** (13.32945)	1.176195*** (14.60699)
	4	**Call**	-0.08605*** (-2.95483)	-0.03118 (-0.7982)	-0.02331 (-0.64729)
		Put	1.018337*** (13.57769)	1.391077*** (13.142)	1.416613*** (14.49322)

Figures in parentheses are t-statistics. The relevant 1%, 5% and 10% critical values are 2.462, 1.699 and 1.311 respectively.

Most of the percentage deviations presented in Table 3.3 are significant at the 1% level indicating that the Black Scholes price is consistently different to the market price across call and put options. The relationship is also robust to the measure of volatility.

It is clear from the results presented in Table 3.3 that the Black-Scholes model consistently underprices FTSE100 put options and consistently overprices the corresponding calls. In general, there is a significant deviation of the observed price from the theoretical price.

Table 3.4 Percentage Deviation of Theoretical Black-Scholes-Merton Price from Synthetic Call Premium and Actual Put Premium 2001

Maturity	M	Contract	Mean Pricing Error		
			Standard Deviation	EWMA	GARCH
Mar	1	Call	-0.22485*** (-10.0131)	-0.20051*** (-13.9985)	-0.19631*** (-12.4128)
		Put	0.365665*** (8.7304)	0.454519*** (16.32939)	0.46278*** (16.57386)
	2	Call	-0.25119*** (-9.97842)	-0.22327*** (-14.0076)	-0.21881*** (-12.3959)
		Put	0.422698*** (8.535601)	0.531994*** (15.9558)	0.54054*** (16.3128)
	3	Call	-0.27856*** (-9.95092)	-0.24719*** (-14.0009)	-0.24245** (-12.3626)
		Put	0.4935*** (8.515349)	0.629576*** (15.34685)	0.637888*** (16.0083)
	4	Call	-0.3086*** (-10.0855)	-0.27419*** (-14.3052)	-0.26915*** (-12.5862)
		Put	0.580873*** (8.583309)	0.750963*** (14.98669)	0.758451*** (15.98649)
Jun	1	Call	-0.24173*** (-8.6783)	-0.34884*** (-30.4796)	-0.32512*** (-24.2798)
		Put	0.117085*** (3.195552)	-0.08531*** (-8.27877)	-0.04147*** (-3.52642)
	2	Call	-0.2737*** (-8.82722)	-0.38921*** (-30.0424)	-0.36419*** (-24.148)
		Put	0.13721*** (3.210466)	-0.0915*** (-7.84735)	-0.04299*** (-3.15489)
	3	Call	-0.30682*** (-8.94525)	-0.43059*** (-29.5385)	-0.40444*** (-23.9531)
		Put	0.164891*** (3.326583)	-0.09405*** (-6.89272)	-0.04031*** (-2.51973)
	4	Call	-0.34364*** (-9.1783)	-0.47475*** (-29.5221)	-0.44463*** (-23.8088)
		Put	0.203184*** (3.579858)	-0.09078*** (-5.79069)	-0.03107* (-1.69992)
Sep	1	Call	-0.28464*** (-32.6512)	-0.09776*** (-5.51194)	-0.09551*** (-5.55873)
		Put	0.298283*** (16.47048)	0.579819*** (15.14959)	0.585589*** (16.10146)
	2	Call	-0.31351*** (-33.418)	-0.10682*** (-5.20942)	-0.10423*** (-5.2471)
		Put	0.341695*** (15.8637)	0.691287*** (14.89256)	0.698276*** (15.83212)
	3	Call	-0.34597*** (-34.1399)	-0.11914*** (-5.04322)	-0.11622*** (-5.07327)
		Put	0.396187*** (15.34002)	0.830275*** (14.83049)	0.838799*** (15.77191)
	4	Call	-0.38155*** (-35.3146)	-0.13479*** (-5.03818)	-0.13156*** (-5.06672)
		Put	0.459612*** (14.48115)	1.000369*** (14.38363)	1.010611*** (15.27393)

Figures in parentheses are t-statistics. The relevant 1%, 5% and 10% critical values are 2.462, 1.699 and 1.311 respectively.

The results in Table 3.4 are not too dissimilar to those in 3.3 in that there is significant divergence between the theoretical and observed price. Puts are consistently undervalued by the Black Scholes model whilst calls are consistently overpriced. The underpricing of puts becomes quite extreme towards the end of the period.

Table 3.5 Percentage Deviation of Theoretical Black-Scholes-Merton Price from Synthetic Call Premium and Actual Put Premium 2002

Maturity	M	Contract	Mean Pricing Error		
			Standard Deviation	EWMA	GARCH
Mar	1	Call	-0.23962*** (-16.8683)	0.113127 (0.41604)	0.093055*** (7.40327)
		Put	-0.11018*** (-5.58272)	0.384641 (1.241955)	0.354485*** (22.43448)
	2	Call	-0.28321*** (-19.0338)	0.122193 (0.425572)	0.097451*** (6.991132)
		Put	-0.09689*** (-3.95283)	0.513428* (1.528226)	0.473333*** (26.02847)
	3	Call	-0.33055*** (-20.9878)	0.129706 (0.414861)	0.099603*** (6.043049)
		Put	-0.08114*** (-2.67045)	0.674614** (1.74372)	0.621073*** (25.82853)
	4	Call	-0.37901*** (-22.8729)	0.138089 (0.412609)	0.101896*** (5.42408)
		Put	-0.05586* (-1.4943)	0.889961** (1.992573)	0.817758*** (25.51367)
Jun	1	Call	0.087238*** (9.517713)	0.229344*** (9.98592)	0.169536*** (9.270732)
		Put	0.467739*** (31.93452)	0.727667*** (17.86314)	0.615905*** (19.69386)
	2	Call	0.087377*** (8.261485)	0.270695*** (9.205573)	0.191947*** (8.384807)
		Put	0.618183*** (29.83411)	0.983692*** (17.45122)	0.822707*** (19.49254)
	3	Call	0.087704*** (7.480335)	0.321305*** (8.730219)	0.218875*** (7.847843)
		Put	0.822938*** (27.06769)	1.34426*** (16.79124)	1.108669*** (18.98475)
	4	Call	0.085527*** (6.288785)	0.379921*** (8.205459)	0.248168*** (7.243019)
		Put	1.105842 (24.15011)	1.86481*** (15.73663)	1.512446*** (17.94232)

Figures in parentheses are t-statistics. The relevant 1%, 5% and 10% critical values are 2.462, 1.699 and 1.311 respectively.

One striking feature of the results presented in Table 3.5 is that for the March contract the Black Scholes model overprices put and call options yet underprices put and call options for the June contract. This is in sharp contrast to estimates produced in other periods and corresponds to the inclusion of extreme market volatility around September 11th 2001 and the subsequent recovery of markets at the beginning of 2002.

The results of the presented in Tables 3.3 to 3.5 demonstrate that there is a significant difference between the Black Scholes price and the market price of FTSE100 options. This mispricing relationship is robust to the choice of volatility measure. This implies that either the Black-Scholes model for the pricing of index options is misspecified or that the method used to calculate volatility is inappropriate. Although a further problem could be the non-synchronicity of the option price and the index level, this would not be able to account for deviations of this magnitude.[19]

The most obvious empirical tests of the Black-Scholes model seek to determine whether predicted prices are biased relative to the observed market prices. Early work by Galai (1977) and Bhattacharya (1983) examined CBOE data and each study found evidence to suggest that the Black-Scholes model accurately predicts call option prices. Although in Bhattacharya (1980) evidence is presented that suggests that at-the-money options close to maturity are overvalued by Black-Scholes. However, Macbeth and Merville (1979) find that, for six major companies listed on CBOE, the Black-Scholes model underprices in-the-money and overprices out-of-the-money options. This mispricing increases with the extent to which the option is in- or out-of-the-money. Furthermore, when options have less than ninety days to

[19] The FTSE100 index is computed on a continuous basis so that the published closing price is exact at that time. However, the closing option price represents the value at the time of the last trade.

maturity out-of-the-money options are still overpriced but there is no apparent relationship between the degree of mispricing and moneyness. Clearly there are a number of similarities between the findings Macbeth and Merville and the results presented above.

The results in this section should be interpreted with caution. One of the key problems with a Black-Scholes analysis is the estimation of the underlying volatility. The measure employed in this study shows that annual volatility increases steadily from 17.9884% on 1st November 1999 to 30.6054% on 13th May 2002. It may well be the case that traders are using their own expectations of volatility to value options rather than historical volatility. Hence an analysis of the volatility implied by observed out-of-the-money option prices may be deemed more appropriate when evaluating crash expectations.

The Black-Scholes-Merton results for the comparison period, when the UK market experienced sustained growth, are displayed in Table 3.6. The reported statistics are displayed in the same way as those in Table 3.3.

Table 3.6 Mean Pricing Error of Theoretical Black-Scholes-Merton Price from Synthetic Call Premium and Actual Put Premium 1998-99

			Standard Deviation	**EWMA**	**GARCH**
Sep 1998	**1**	**Call**	-0.08283*** (-7.62811)	-0.07845*** (-6.56102)	-0.10944*** (-10.9658)
		Put	1.643844*** (48.47593)	1.686216*** (34.40061)	1.45497*** (39.83742)
	2	**Call**	-0.07341*** (-5.76205)	-0.06779*** (-4.80383)	-0.10558*** (-9.14467)
		Put	1.975519*** (46.2399)	2.034023*** (31.76765)	1.732687*** (37.41437)
	3	**Call**	-0.06361*** (-4.2554)	-0.05647 (-3.38739)	-0.10217*** (-7.69191)
		Put	2.393994*** (44.22404)	1.293633*** (27.79017)	2.078694*** (35.90524)
	4	**Call**	-0.05534*** (-3.16592)	-0.04647** (-2.38432)	-0.10107*** (-6.62524)
		Put	2.922529***	3.032877***	2.510256***

			(41.39336)	(28.20637)	(33.58543)
Dec 1998	**1**	**Call**	0.063881* (1.429734)	0.080073* (1.677516)	-0.0352 (-0.94391)
		Put	0.552932*** (8.017754)	0.583337*** (7.684102)	0.355711*** (6.462787)
	2	**Call**	0.066327* (1.313237)	0.074121* (1.444868)	-0.0528* (-1.33712)
		Put	0.657901*** (7.937833)	0.678741*** (7.757917)	0.414115*** (6.643655)
	3	**Call**	0.063263* (1.140129)	0.072556 (1.273204)	-0.06761* (-1.5682)
		Put	0.771898*** (8.09918)	0.797126*** (7.872861)	0.487018*** (6.89512)
	4	**Call**	0.046412 (0.796021)	0.056084 (0.945569)	-0.09512** (-2.14531)
		Put	0.906162*** (8.18189)	0.93718*** (7.902101)	0.572261*** (7.051992)
Mar 1999	**1**	**Call**	0.103537*** (7.796546)	0.09257*** (6.627509)	0.264118*** (12.32667)
		Put	0.521427*** (26.57038)	0.501089*** (24.36819)	0.841386*** (20.7892)
	2	**Call**	0.106279*** (7.291718)	0.093858*** (6.137221)	0.288844*** (11.90083)
		Put	0.596922*** (25.89954)	0.572834*** (24.25682)	0.974914*** (20.80191)
	3	**Call**	0.105818*** (6.580957)	0.091854*** (5.464987)	0.312127*** (11.29846)
		Put	0.684251*** (25.14716)	0.655492*** (24.35574)	1.132334*** (20.87296)
	4	**Call**	0.101045*** (5.744334)	0.085474*** (4.661918)	0.332543*** (10.63762)
		Put	0.793499*** (22.18986)	0.758966*** (21.98047)	1.328419*** (20.23561)
Jun 1999	**1**	**Call**	-0.1297*** (-14.0303)	-0.11987*** (-10.7305)	-0.00965 (-0.51079)
		Put	0.325314*** (23.28968)	0.306215*** (8.025557)	0.569259*** (9.641578)
	2	**Call**	-0.14999*** (-14.7617)	-0.13886*** (-11.0323)	-0.01397 (-0.64691)
		Put	0.384464*** (23.73105)	0.470727*** (11.38544)	0.807752*** (12.11884)
	3	**Call**	-0.17204*** (-15.5926)	-0.15961*** (-11.5626)	-0.01913 (-0.7886)
		Put	0.449526*** (23.67573)	0.757762*** (8.068858)	1.20226*** (9.899317)
	4	**Call**	-0.19796*** (-16.1123)	-0.18428*** (-12.1378)	-0.02749 (-0.9995)
		Put	0.524498*** (24.52272)	0.617423*** (9.829967)	1.089912*** (12.40753)

Figures in parentheses are t-statistics. The relevant 1%, 5% and 10% critical values are 2.462, 1.699 and 1.311 respectively.

The results presented in Table 3.8 illustrate a significant and consistent relationship. The Black-Scholes model consistently undervalues FTSE100 puts and overprices FTSE100 calls with matching maturity and moneyness. In this respect there is no discernable difference between Black-Scholes pricing in the period of sustained growth relative to the dot com bubble period. The pricing errors for puts when using a GARCH model are particularly large during this period. Assuming that it is the measures of volatility that are inappropriate, it is once again proposed that, in respect to this period, analysis of the volatility implied by observed price out-of-the-money put and call options will be a more robust measure of trader expectations than Black-Scholes prices.

3.4.2 Implied Volatilities

Table 3.7 Mean Implied Volatilities of Out-of-the-Money Puts and Calls Written on the FTSE100 Stock Index

OTM	1		2		3		4	
	Call	Put	Call	Put	Call	Put	Call	Put
Jan 00	0.107943	0.198565	0.109988	0.199899	0.110155	0.201732	0.110518	0.202965
Mar 00	0.120825	0.248439	0.123434	0.24947	0.127046	0.252251	0.128765	0.254009
Jun 00	0.104879	0.235536	0.109828	0.236014	0.113547	0.237136	0.116094	0.23856
Sept 00	0.049822	0.197425	0.051765	0.195424	0.063455	0.194025	0.072713	0.193257
Dec 00	0.126489	0.197573	0.127405	0.197867	0.127601	0.198785	0.127672	0.201252
Mar 01	0.076433	0.198813	0.083597	0.198165	0.088401	0.197999	0.091812	0.19976
Jun 01	0.097473	0.201594	0.101659	0.201097	0.104771	0.201146	0.106812	0.201801
Sept 01	0.089537	0.205087	0.094873	0.204487	0.098537	0.204365	0.101147	0.204336
Mar 02	0.116908	0.176398	0.117572	0.178362	0.117938	0.180002	0.118273	0.182056
Jun 02	0.094056	0.161983	0.095135	0.162798	0.096093	0.164116	0.096751	0.165947

The results presented in Table 3.7 illustrate the temporal behaviour of implied volatility throughout the period under analysis. Casual inspection indicates that put implied volatility exceeds call implied volatility for all observations in this sample. It follows that clearer information regarding traders' expectations will be revealed by investigating the **difference** between put and call implied volatility. In order to examine the difference an implied volatility, a volatility spread is constructed by subtracting the mean implied volatilities of synthetic call options from those of put options with matching maturity and moneyness. Implied volatility spreads for options written on the FTSE100 are displayed in Table 3.8. Numbers 1-4 again correspond to the moneyness presented in Table 3.0.

Table 3.8 Implied Volatility Spreads for Out-of-the-Money Puts and Calls Written on the FTSE100 Stock Index

IVSpread $= IV_p - IV_c$

OTM	1	2	3	4
Jan 00	0.090622	0.089911	0.091577	0.092446
	(71.44901)	(59.62808)	(63.52901)	(81.9978)
Mar 00	0.127614	0.126036	0.125205	0.125243
	(167.0703)	(155.9025)	(141.2925)	(137.2412)
Jun 00	0.130656	0.126186	0.123589	0.122466
	(38.57693)	(38.14701)	(38.02901)	(37.71499)
Sept 00	0.147604	0.143659	0.13057	0.120543
	(74.10899)	(106.6259)	(113.0491)	(60.70172)
Dec 00	0.071084	0.070462	0.071183	0.07358
	(66.67611)	(67.13618)	(63.87211)	(8.374759)
Mar 01	0.12238	0.114568	0.109598	0.107948
	(130.3315)	(78.28705)	(58.8858)	(29.34284)
Jun 01	0.104121	0.099438	0.096374	0.094989
	(184.3499)	(116.5411)	(83.14302)	(68.96197)
Sept 01	0.115549	0.109614	0.105828	0.103189
	(122.6069)	(98.95484)	(87.35733)	(72.41275)
Mar 02	0.05949	0.060789	0.062063	0.063783
	(92.02617)	(98.38111)	(93.77489)	(84.04012)
Jun 02	0.067926	0.067663	0.068022	0.069196
	(91.95034)	(111.9607)	(143.1126)	(155.012)

Figures in parentheses are t-statistics. All values are significant at the 1% level.

All of the figures presented in Table 3.8 are significant and positive. This means that the implied volatility of puts exceeds the implied volatility of calls throughout the period. There is however evidence that the volatility smile evolves through time. The implied volatility of puts relative to calls increases as we move from the January 2000 contract through the September 2000 contract. Following a narrowing of the volatility spread for the December 2000 contract the implied volatility spread exceeds 10 percentage points until it narrows in 2002. Notably, moneyness seems to have little impact on the magnitude of the spread during this period.

A sample of call and put implied volatility smirks are presented in Figure 3.4, Panels A to F, to accompany the discussion of unorthodox preferences and the risk-neutral distribution. The volatility smirks provide a graphic illustration of the behaviour of implied volatility over time. It is clear that put implied volatility exceeds that of calls with matching moneyness. There is also a pronounced skew with volatility increasing as options are observed further out-of-the-money.

Table 3.9 Mean Implied Volatilities of Out-of-the-Money Puts and Calls Written on the FTSE100 Stock Index Comparison Period

OTM	1		2		3		4	
	Call	Put	Call	Put	Call	Put	Call	Put
Sept 98	0.079327	0.251099	0.074906	0.250355	0.084159	0.249994	0.090227	0.249804
Dec 98	0.126489	0.197573	0.127405	0.197867	0.127601	0.198785	0.127722	0.200129
Mar 99	0.209092	0.313832	0.208485	0.315207	0.207376	0.316696	0.205729	0.319163
Jun 99	0.112274	0.214564	0.114101	0.215656	0.115566	0.216464	0.116477	0.217312

Table 3.9 illustrates the temporal behaviour of implied volatility throughout the comparative period. Perhaps the most notable feature of these results is the increase in implied volatility used to price both put and call options maturing in March 1999 with a subsequent fall in each for the contract maturing in June 1999. On initial inspection this pattern indicates that traders are concerned about the future volatility of the market index and are hence using high estimates of implied volatility to price options. However, at this stage it is not possible to infer the direction of expected price changes that dominates.

Again, more information may be revealed by investigating the volatility spread calculated from mean implied volatilities obtained from symmetrically distributed put and synthetic call option prices. These are displayed in Table 3.10. Numbers 1-4 denote the moneyness as defined in Table 3.0 for the nearest to fourth-nearest out-of-the-money contracts respectively.

Table 3.10 Implied Volatility Spreads for Out-of-the-Money Puts and Calls Written on the FTSE100 Stock Index Comparison Period

OTM	1	2	3	4
Sept 98	0.171773	0.175449	0.165835	0.159577
	(22.75996)	(134.5161)	(165.6162)	(178.5459)
Dec 98	0.071084	0.070462	0.071183	0.072407
	(66.67611)	(67.13618)	(63.87211)	(63.54049)
Mar 99	0.104739	0.106723	0.10932	0.113434
	(111.8539)	(112.0037)	(117.1441)	(117.1602)
Jun 99	0.10229	0.101556	0.100898	0.100834
	(242.9502)	(199.9458)	(171.778)	(174.9911)

Figures in parentheses are t-statistics. All values are significant at the 1% level.

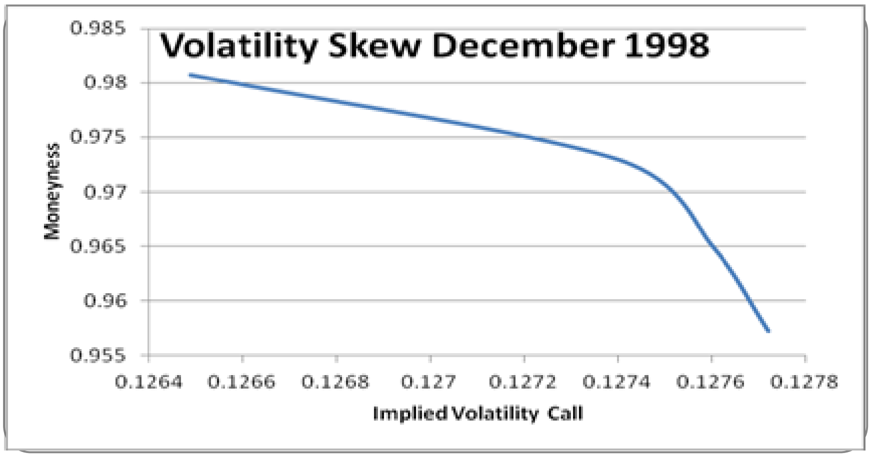
The results in presented in Table 3.10 illustrate that the volatility spread is positive and significant throughout the period of sustained market growth. The spread narrows somewhat in respect to the contract that matures in December 1998. Nevertheless, put implied volatility consistently sits above call implied volatility throughout the period. As the period under consideration follows a sustained period of market growth, the results would appear to suggest that 'normal' stock index option pricing behaviour in the UK market is characterised by a put/call premium. In other words, traders price out-of-the-money puts higher than equally out-of-the-money calls with the same expiration date and written on the same underlying asset. This finding is consistent with the assertion of Chen, Hong and Stein (2001) and Rubinstein (1994) that, since the crash of October 1987, traders have been overly concerned about the possibility of a crash and price options according to these concerns.

3.5 Volatility Smiles and the Risk Neutral Distribution

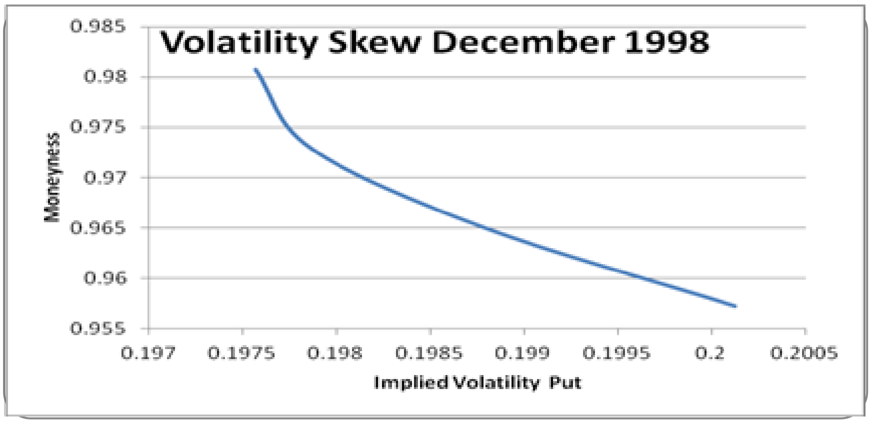
The results presented in the previous sections clearly indicate that the Black-Scholes model encounters problems in pricing FTSE100 index options. Jackwerth and Rubinstein (2003) identify similar problems for the model in pricing US index option prices. The Black Scholes model is built on the assumption that the risk-neutral probability distribution is lognormal with mean and variance determined by the riskless rate of interest and implied volatility. Under the Black-Scholes model the volatility smile should be flat. Whilst the volatility smile is less pronounced for individual equity options, there is clear evidence of a smile in index implied volatility. A sample of the volatility smiles taken from the previous section, presented in Figure 3.4 panels A to F illustrate that there is a pronounced skew in FTSE100 index options.

Figure 3.4 Implied Volatility Smiles

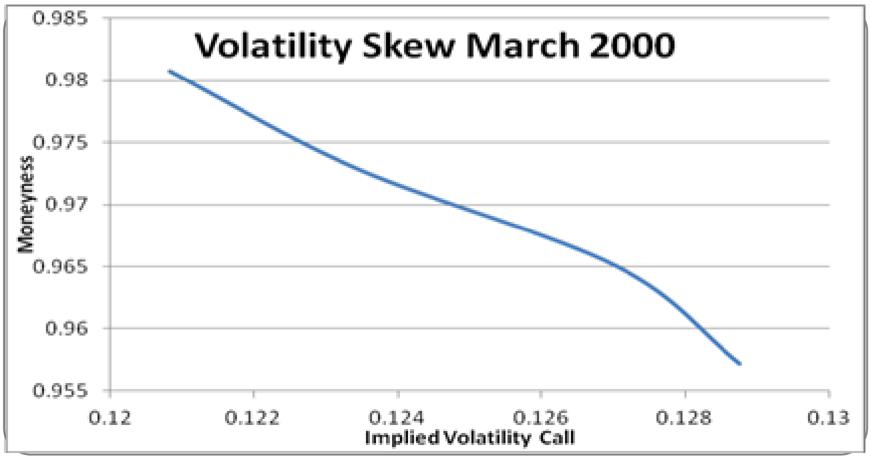
Panel A



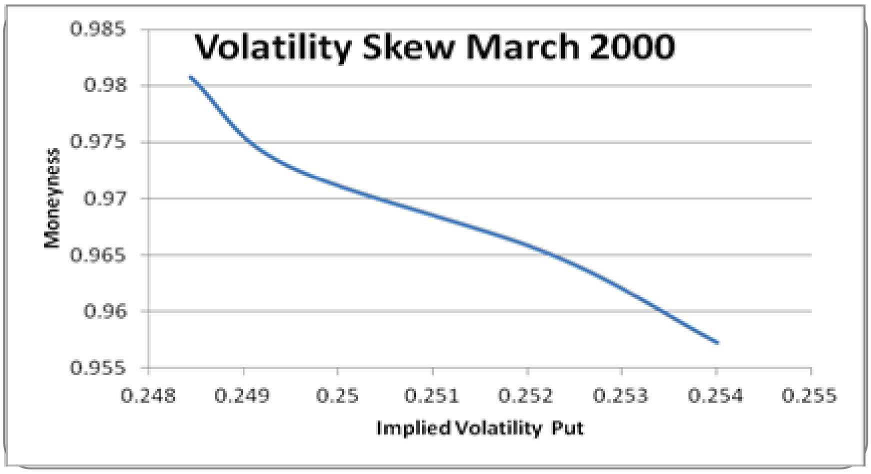
Panel B



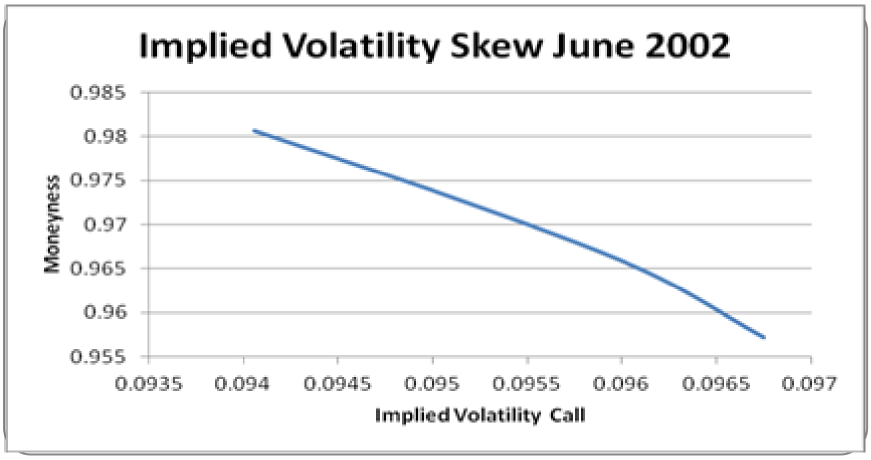
Panel C



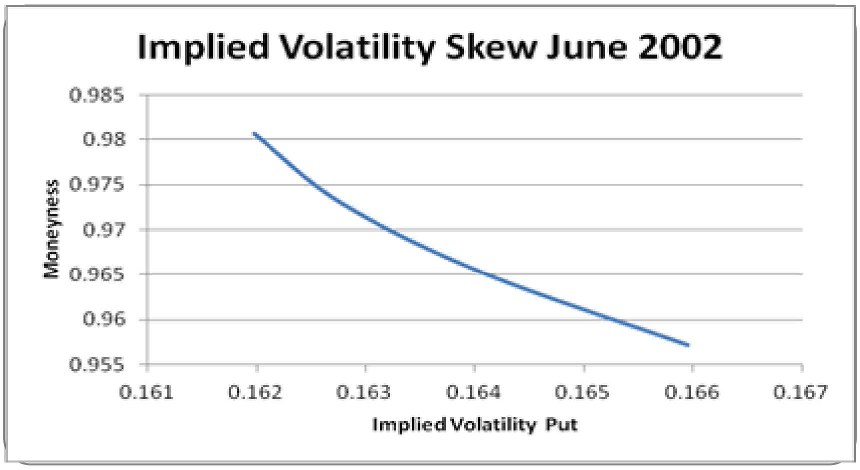
Panel D



Panel E



Panel F



The panels in Figure 3.4 clearly illustrate the relationship between put and call implied volatility for FTSE100 options and demonstrate that option pricing models that assume a lognormal risk-neutral distribution will produce pricing errors.

Jackwerth (2000) derives risk aversion functions from S&P500 options and finds that there is a significant change in these functions around the time of the 1987 stock market crash. He argues that the change in the shapes of risk aversion functions is most likely to be caused by mispricing in the options market. Jackwerth derives investor preferences from the risk neutral and subjective probability distributions. The risk neutral distributions are recovered from option prices using the authors own method from Jackwerth and Rubinstein (1996). Prior to the crash the risk neutral distribution is lognormal however the risk neutral distribution after the crash is left-skewed and leptokurtic. The actual distribution, which proxies for the subjective distribution, remains lognormal across both periods. If investors were indifferent to risk then these probabilities would be identical. As risk aversion functions are constructed from the two distributions it follows that the risk aversion functions must also have changed from the pre-crash to the post-crash period. Concerns about the probability of a crash may lead to investors updating their beliefs regarding the distribution of market returns by too much. This in turn will lead to a left skewed risk neutral distribution and produces a steep volatility smile and put options that are overpriced. Hence loss aversion as identified in Chapter 1, particularly aversion to significant losses skews the risk neutral distribution resulting in put options that are highly priced relative to similarly out-of-the-money calls.

Jackwerth and Rubinstein (2003) provide further insights into the inefficiency of the S&P500 index options market in light of the model-dependent finding that the market exhibits a preference for risk post-1987. Jackwerth and Rubinstein test the hypothesis of inefficiency by constructing a strategy where S&P500 options are continually rolled over. This strategy is found to yield abnormal risk-adjusted profits. Jackwerth and Rubinstein demonstrate that the risk-neutral, post 1987 crash, distribution is negatively skewed with higher leptokurtosis than a lognormal distribution. The most compelling arguments for the shape of the risk-neutral distribution are that options are mispriced and that, due to limited arbitrage, these mispricings are not corrected,

Rosenberg and Engle (2002) investigate the characteristics of investor risk aversion across different states of the market. They estimate a time-varying pricing kernel to produce a risk-neutral distribution that is less leptokurtic and less left-skewed than that of Jackwerth (2000). They estimate their empirical pricing kernel using S&P500 index prices and option payoff probabilities. The empirical pricing kernel is then the preference function that best fits actual prices. Rosenberg and Engle's results demonstrate that investors become more risk averse during recessions and less risk averse during periods of growth. This is demonstrated by examining the correlation between empirical risk aversion and the width of the credit spread and also with the steepness of the term structure slope. They find negative correlation with the former and positive with the latter.

Bondarenko (2003) attempts to explain what he terms the 'overpriced puts puzzle' in an equilibrium framework as opposed to the partial equilibrium frameworks of Hull and White (1987) and Heston (1993). To contextualise the extent of put expensiveness he notes that for S&P500 at-the-money puts to break even, crashes of the magnitude of the 1987 crash would need to occur 1.3 times per year. More importantly the trade in puts accounts for a significant transfer of wealth from buyers to sellers. Bondarenko argues that Jackwerth's kernel pricing puzzle may be spurious as it is wrongly based on the assumption that the pricing kernel is a function of the value of the market portfolio. He also finds that standard equilibrium models (CAPM and Rubinstein (1976)) are incompatible with the level of put prices. Bondarenko uses a model-free equilibrium approach where the fair compensation for taking the risk involved in writing puts depends on a non-standard equilibrium model of risk and return and incorporates a rationality restriction. The risk neutral distribution is estimated non-parametrically from S&P500 option prices. However, the model is unable to explain the high price of put options.

The literature which uses unorthodox preferences, such as loss aversion and time-varying risk-aversion, to explain the shape of the risk-neutral distribution goes some way towards explaining the shape and the evolution of the volatility smile for index options.

3.5 Conclusion

The analysis of FTSE100 put and call option prices matched by moneyness and maturity fails to provide any conclusive evidence of return predictability for the FTSE100 index. Puts are priced more highly than calls during the dot com bubble boom and burst around the turn of the century. However, the relationship is found to be comparable during a period of sustained growth. Over the entire period it is apparent that there is no consistent way in which market moves can be predicted using stock index option prices hence market efficiency cannot be rejected on these grounds.

The Black-Scholes model, which assumes a lognormal risk-neutral distribution, significantly undervalues puts and overvalues calls across the period under investigation. The only exceptions occur in a short period across the final quarter of 2001. The finding of under- and overvaluation is robust across four different moneyness categories and to the use of static and time-varying volatility estimates. This finding motivates an analysis of implied volatility and implied volatility spreads. The volatility spreads indicate that implied volatility of FTSE100 puts lies consistently above that of corresponding calls. The implied volatility itself indicates a pronounced volatility skew which is clear from the charts in section. 3.5. The evolution of the smile does not imply predictability but it does appear that options market investors react to events in the market. For example the highest put implied volatility is observed for the contract which matures in March 2000. The option prices used in backing out this implied volatility were observed in January and February of 2000, immediately after the bubble burst.

The apparent mispricing of FTSE100 options indicates that there are implicit crash fears in the UK market and these pre-date the dot com bubble. The shape of the volatility smiles indicate that option investors are loss-averse and particularly averse to the extreme losses that can be suffered as a result of a crash. When implicit crash fears are priced, option prices reveal a risk-normal distribution which is not lognormal. Hence it is unsurprising that there are significant pricing errors when a Black-Scholes model is used to price FTSE100 index options.

Generally, it seems that traders' fear of downside risk dominates their perception of upside potential. Put simply, traders are aware that market crashes occur and, when they do, losses are likely to be substantial. Thus, the put option premium is analogous to an insurance policy against a significant event that has been witnessed in recent history. Overall, the results presented in this chapter provide motivation of a more in-depth analysis of implied volatility in UK markets.

Chapter 4

Was the 2007 Crisis Expected?

An Analysis of Implied Volatility in UK Index Options Markets

4.1 Introduction and Motivation

The first major financial crisis of the 21st century began in mid-2007 when the losses associated with subprime lending became apparent. This was quickly followed by events such as the closure of Dillon Reed, bailout of Bear Stearns' hedge funds, bankruptcy of American Home Mortgages, plight of Northern Rock, bailout of AIG and collapse of Lehman Brothers.[20] In an efficient capital market the assumption would be that the financial crisis and credit crunch could not have been predicted; it was new information that would be impounded into prices as soon as it became publicly available. However it is clear that the seeds of the crisis were sown in the years prior to 2007 which raises the question as to whether professional option traders may have anticipated the crisis.

As discussed in Chapter 3, if option traders were privy to information prior to an extreme market event, or period of turbulence regarding the probability of such an event occurring, then clearly this would be priced into option premiums. More precisely, the demand for stock index put options would exceed that for stock index calls with a similar degree of moneyness. Option writers would react to the higher demand and perceived information signal and adjust the prices of index options accordingly. If investors are able to anticipate financial crises then this will allow them to re-balance their portfolios and hence insulate them from the most damaging impacts. The availability of volatility indexes and their interpretation as a gauge of investor sentiment provides an additional means by which to analyse market predictability.

An alternative approach to that employed in Chapter 3 is taken in Chapter 4 where the focus will be on implied volatility indexes such as the VIX and VFTSE. Index

[20] Pilbeam (2010) provides a detailed timeline of key events in the financial crisis.

option implied volatility incorporates investor expectations and, if investor expectations turn out to be correct on average, it should provide a useful predictor of future spot market behaviour. Furthermore, implied volatility is a widely recognised and important gauge of expected future volatility as investors are considering options which mature over a range of future exercise dates. This chapter provides an important contribution to the literature as a unique volatility index is constructed to facilitate examination of the relationship between implied volatility and the UK stock market prior to the introduction of the VFTSE in 2008.

This key objective of this chapter will be to examine and seek to address a number of important questions:

- Do the contemporaneous relationships between volatility indexes and UK stock market returns support the notion of 'fear indexes'?
- Do volatility indexes contain any predictive power for the actual, or realised, volatility of stock indexes?
- Do volatility indexes contain any predictive power for aggregate stock market returns?
- To what extent can volatility indexes provide an insight into investor sentiment before, during and after the recent financial crisis?

4.2 Literature Review

The VIX is the Chicago Board Options Exchange (CBOE) volatility index which calculates the implied volatility of American-style S&P 500 options over a 30-day horizon. It is a weighted average of the implied volatilities of eight call and put options which are close-to-the-money. The VIX serves as an indicator of optimism and pessimism and hence is sometimes referred to, for example by Whaley (2000), as the 'fear indicator'. Simon (2003) adds that the level of the VIX indicates the price investors are willing to pay in terms of implied volatility to hedge stock portfolios with index put options or to take long positions in index calls. Moreover Simlai (2010) expands the notion of the VIX as a fear index to a barometer of investor sentiment in both bullish and bearish markets. It can be interpreted as market participants' consensus view of expected future stock market volatility.

A number of studies have used implied volatility as a means to predict future volatility. Prominent articles are those by Day and Lewis (1992), Lamoureux and Lastrapes (1993), Fleming (1998) and Christensen and Prabhala (1998).

Day and Lewis (1992) compare the volatility forecasting performance of Black-Scholes-Merton implied volatility extracted from S&P 100 stock index options with forecasts produced using GARCH models on weekly data. They find that implied volatility may offer incremental information relative to conditional volatility provided by GARCH and EGARCH models and vice versa. This indicates that neither method completely characterises in-sample stock market volatility.

Lamoureux and Lastrapes (1993) investigate the implied volatility of at-the-money call options using the Hull and White (1987) stochastic volatility model and compare its forecasting performance with that of a GARCH model. Lamoureux and Lastrapes extend the work of Day and Lewis by investigating daily data on individual stock options traded on the CBOE between 1982 and 1984 and by testing an out-of-sample model. Lamoureux and Lastrapes reject the option pricing model as a price-determining market mechanism but do find that the model can be adjusted to provide important information for forecasting stock variance over a 90 to 180 day horizon.

Canina and Figlewski (1993) investigate the informational content of implied volatility extracted from American-style S&P 100 options. Closing prices for the sample period March 1983 to March 1987 are input into a binomial option pricing model. The implied volatilities produced exhibit a clear volatility skew. Canina and Figlewski's key finding is that implied volatility is not a good estimate of the market expectation of realised volatility. Furthermore implied volatility is incorporated into past volatility which, in turn, is significantly related to future volatility. However the bulk of the subsequent literature contradicts these findings. Christensen and Prabhala (1998) use monthly observations over a longer time period to produce evidence in contrast to that of Canina and Figlewski. Christensen and Prabhala also investigate S&P 100 implied volatility but use non-overlapping data for the period November 1983 to May 1995. The authors find that, despite producing biased forecasts, implied volatility does predict realised future volatility and incorporates historical volatility. Furthermore, the predictive power of implied volatility is found to improve following the 1987 stock market crash. Jorion (1995) produces evidence from currency options that contrasts with that of Canina and Figlewski. He finds that implied volatility estimates outperform GARCH models in forecasting future volatility.

Fleming (1998) also considers the implied volatility of S&P 100 options and compares this to historical volatility and conditional volatility produced by GARCH models. Fleming finds that implied volatility produces biased forecasts although it is unclear whether this is a result of option market inefficiency or misspecification of the volatility process in the option pricing model. He also finds that implied volatility produces useful estimates of future volatility which are independent of those produced by a GARCH model. Fleming concludes by highlighting the importance of implied volatility as a measure of investor sentiment, a potential input for asset pricing and an indicator of expected returns.

Fleming, Ostdiek and Whaley (1995) examine the predictive power of the VIX for future realised stock market volatility. They perform their analysis on daily and weekly returns on the S&P 100 index and changes in the VIX over the period 1986 to 1992. Fleming *et al* find evidence of significant negative contemporaneous correlation between changes in the VIX and returns on the S&P 100. Hence high volatility is associated with negative stock market moves and vice versa. Interestingly the effect is asymmetric with larger absolute changes in volatility associated with negative returns as opposed to positive returns of equivalent magnitude. Fleming *et al* also find the VIX to be a good predictor of realised future stock market volatility and add that it imbeds the expectations of market participants.

Blair, Poon and Taylor (2001) compare the predictive ability of implied volatility with that of ARCH models using daily data on the VIX and S&P 100. They also use high frequency intraday data on the index to compute a measure of realised volatility. The sample period is from January 1987 to December 1999. The authors also consider how important the choice of measure of realised volatility is to the predictive power of volatility forecasts. Blair, Poon and Taylor find that in-sample ARCH models provide no additional information on index returns over and above that provided by the VIX. Moreover little further information is produced by the inclusion of the high frequency returns. For out-of-sample forecasts the VIX outperforms all other methods tested in terms of accuracy.

Martens and Zein (2004) consider volatility forecasts using publicly available high frequency data. The S&P 500 index and associated option contract is examined along with currency futures and options on the YEN/USD and on crude oil. Martens and Zein's findings indicate that implied volatility outperforms a GARCH(1,1) model in each case for daily data. For high frequency data the GARCH extended with high volatility forecasts outperforms the GARCH extended with realised volatility. However, when realised volatilities are produced using squared high frequency returns, long memory GARCH forecasts can at least match the performance, and in some cases outperform the implied volatility forecasts. Martens and Zein note that each type of forecast contains information which is not contained in the other.

A further comparative analysis based on the S&P 100 and the VIX is conducted by Koopman, Jungbacker and Hol (2005) who employ intraday data. Koopman *et al* investigate a variety of models to produce a ranking of volatility forecasts. They conclude that the most accurate forecasts of realised volatility can be produced using an autoregressive fractionally integrated moving average model followed by those produced using an unobserved components model.

Giot (2005) examines both the contemporaneous relationship between implied volatility and returns and the relationship between implied volatility and future returns using daily return data from August 1994 to January 2003. The sample period includes bull and bear markets and periods of high and low volatility. Giot demonstrates that there is a negative and significant relationship between the contemporaneous returns on the S&P 500 index and the VIX and VXN volatility indexes[21]. Giot also found weak evidence of a positive relationship between future returns and implied volatility indexes. Similar relationships were found by Simlai (2010) although the results presented also indicate that there is a strong information flow from the S&P 500 to the VIX. Simlai examines correlations in index option implied volatility using the VIX, the 10-year US T-bill rate and the S&P 500. The period under investigation covers the technology boom from 1995 to 2001. Simlai selects daily data and employs a variety of GARCH models to examine whether the variability of index option implied volatility is driven by market information. The key findings are the aforementioned significant flow of information from the S&P 500 to the VIX and that high implied volatility is associated with falling index values.

Simon (2003) investigates the relationship between the NASDAQ 100 index (NDX) and its associated VXN volatility index. He finds that the response of the VXN to changes in the NASDAQ 100 index is remarkably stable for the duration of the technology stock bubble of the late 1990s/2000 and beyond. In particular the volatility index falls in response to large positive returns on the underlying index and rises in response to large negative returns. However he also finds that, although the VXN has predictive power for actual volatility, it consistently predicts higher volatility than is realised. Furthermore, he finds that over the entire sample period greater positive and negative deviations of the NDX from its 5-day moving average lead to statistically significant greater increases in the VXN. Simon offers reconciliation of this finding with the finding that positive NDX returns are associated with greater VXN declines. He explains that positive returns *per se* reduce fear and hence lead to reduced demand for puts for hedging and for calls in their role as a low risk position in a stock. However sustained upward deviations from a moving average are

[21] The VXN is an index that is constructed from implied volatility of close-to-the-money, near maturity American-style option contracts on the NASDAQ100 index.

perceived as a trend in the NDX. This in turn makes long calls more attractive due to the convexity of delta. Interestingly, during the bubble period negative deviations of the NDX from its 5-day moving average were not associated with higher increases in the VXN. Simon offers a plausible explanation that deviations were not perceived as signalling a downward trend because the overall trend had been overwhelmingly positive. The relationship in the post-bubble period is found to be consistent with that for the entire sample period.

Simon considers why the VXN moves in opposite directions in response to large positive and negative NDX returns and summarises with three key explanations:

1. Implied volatility reflects how actual volatility reacts to positive and negative returns.
2. The VXN is driven by option trading dynamics. The insurance demand for puts and demand for calls as a low-risk equity position rise in response to negative returns on the underlying. During market rallies market participants are inclined to purchase less puts for hedging purposes and are more willing to hold equities as the perception of downside risk is less salient.
3. The commonly observed volatility skew reflects higher implied volatilities for options with low exercise prices. As equity prices rise, at-the-money options have higher exercise prices and lower implied volatilities than those previously at-the-money. As at-the-money options are used to compute volatility indexes, the volatility skew may partly explain the tendency of market rallies to be associated with falling implied volatility and declines with rising implied volatility.

The vast majority of studies of the forecasting power of implied volatility have examined index options whilst there are apparently very few studies published that investigate the information content of implied volatility of single stock options. Notable exceptions are those published by Gemmill and Dickins (1986), Lamoureux and Lastrapes (1993) and Taylor, Yadav and Zhang (2010).

Gemmill and Dickens (1986) examine the prices of equity call options of 16 companies listed on the London traded options market. Their objective is to examine whether the Black Scholes model can be used to identify mispriced options and whether profitable strategies can be constructed as a result. Delta hedged portfolios are constructed which yield significant positive returns, however the positive returns do not survive the inclusion of transactions costs. Hence the market efficiency cannot be rejected for the period under analysis (1978-1983) and inferences are difficult to draw due to non-synchronous trading of stocks and options.

Lamoureux and Lastrapes (1993) employ the Hull and White (1987) model to test the orthogonality restriction that information available when market prices are set is not superior to implied variance in predicting realised return variance using CBOE options and associated stocks. Implied variances are collected from at-the-money call options written on individual stocks whilst a GARCH model is used to predict return variance from market prices. The key findings are that implied variance significantly underpredicts realised variance and that forecasts from past returns contain relevant information additional to that contained in implied variance.

Taylor, Yadav and Zhang (2010) adopt a model-free approach to investigate the information content of implied volatility for 149 US firms for the period January 1996 to December 1999. The advantage of selecting a model-free approach is that such approaches permit analysis of implied volatility that does not rely on, and hence does not suffer from the limitations of, any option pricing model. Taylor *et al* find that volatility from historical prices, at-the-money implied volatility and model-free volatility each contain some, but not all relevant information regarding future return volatility. However the model-free approach is found to be unsatisfactory due to the relative illiquidity of out-of-the-money individual stock options.

The VFTSE was launched in June 2008 to measure implied volatility of FTSE100 index options and is constructed in a similar way to the VIX index. The VFTSE uses implied volatilities of out-of-the-money put and call options written on the FTSE100 index. It is quoted in percentage points and is designed to capture the expected move in the index in the subsequent 30-day period. It therefore provides a useful tool to investigate crash expectations particularly at 1 month horizons. However the introduction is too late to be a useful indicator for the purposes of this study. Hence the VIX will be used as a market wide indicator of investor sentiment.

Note that the introduction of the short sales ban in 2007 may have prevented option traders from fully hedging their positions and hence induced a temporary impediment to the liquidity of the market. However this is likely to be mitigated somewhat by an increased demand for puts as a means of circumventing the short-sales restrictions.

A preliminary assessment of Whaley's interpretation of the VIX as an indicator of investor sentiment can be performed by a graphical inspection of the series. Figure 4.1 presents the end-of-day VIX series in the levels over the period leading up to the crisis, during the crisis and the immediate aftermath. The sample begins on January 3rd 2007 and culminates on December 31st 2009.

Figure 4.1 Time Series Graph of the VIX 2007-2009

It is clear from this preliminary examination that higher implied volatility, represented by the VIX, is associated with fear and pessimism in the financial markets. The mean value of the VIX during this period is 27.26% however the index peaks at 80.86% in October 2008. There is a notable upward trend prior to this date punctuated by spikes associated with key events as the crisis unfolded. There is a clear and steep increase in September 2008 which coincides with Lehman Brothers' filing for bankruptcy on September 15th. It is also clear that the degree of fear in the market subsided considerably following this highly turbulent period and settled at an average of 24.28% for the second half of 2009.

4.3 Initial Tests to Examine the VIX/VFTSE Relationship

4.3.1 Introduction

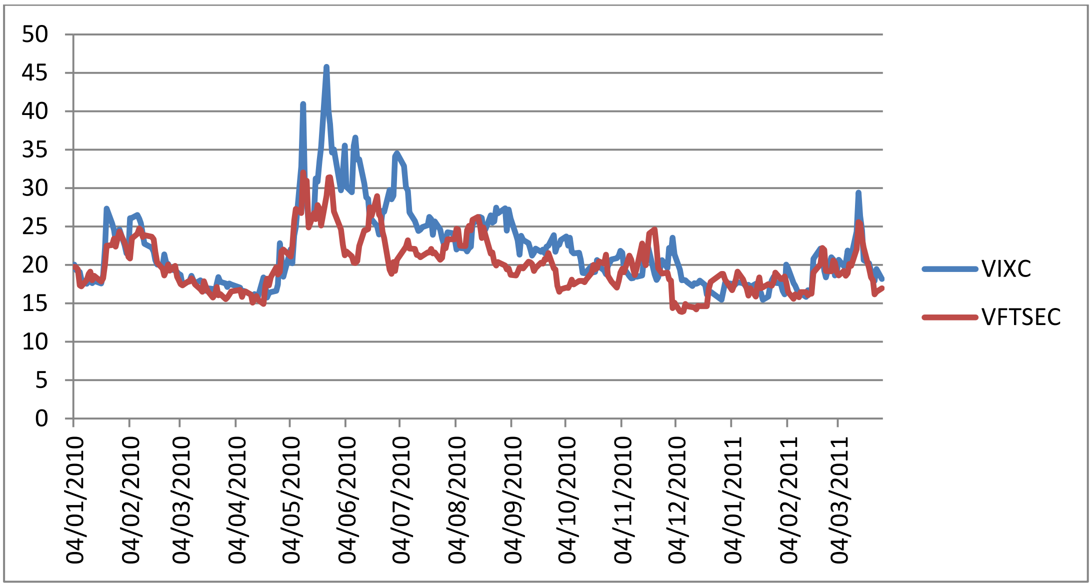
In order to establish whether the VIX is an appropriate proxy for the VFTSE a number of tests were run using daily opening, closing, high and low values, and, more importantly, using the closing value of the VIX on the opening value of the VFTSE. Gemmill and Kamayama (2000) demonstrate, using a vector autoregressive model, that changes in the implied volatility of the UK market on a given day are driven by lagged changes in implied volatility of the US market. This result accords with intuition as the US market closes 6 hours (Central Time in Chicago) after the close of markets in London. It follows that the strongest relationship should be between the opening value of the VFTSE on day n and the closing value of the VIX on day n-1. Gemmill and Kamayama also examine for similar spillover effects using the Nikkei 225.

This range of values examined should mitigate against the non-contemporaneous nature of opening and closing values arising from the time difference between the UK and US.

4.3.2 Data

Historical daily price data for opening, closing, high and low values for the VIX are collected from the Chicago Board Options Exchange (CBOE). Corresponding values for the VFTSE are collected from Euronext LIFFE. It is necessary to select a fairly recent sample period given the limited VFTSE data availability. Hence the data selected cover the period from 4/1/2010 until 29/3/2011. Figure 4.2 provides a visual inspection of the relationship between closing values of the two series:

Figure 4.2 Time Series Graph of the VIX and VFTSE 2010-2011 (Closing)



The shape of each index series is very similar although for most periods implied volatility is higher in the US than in the UK particularly in the major spikes between April and June 2010. It appears that in some periods the VIX leads the VFTSE whilst in others the relationship is reversed. Overall it appears that the VIX moves prior to the VFTSE strengthening the case for examining the relationship between the closing values of the VIX and the opening values of the VFTSE.

The initial test performed was a simple correlation to determine the relationship between the series:

$$\rho_{x,y} = \frac{\sum(x-\bar{x})(y-\bar{y})}{\sqrt{\sum(x-\bar{x})^2 \sum(y-\bar{y})^2}} \qquad (4.1)$$

Running equation 4.1 produced the following coefficients where subscripts indicate opening, closing, high, low and close on open values respectively.

Table 4.1: Correlation Between VIX and VFTSE

	ρ_o	ρ_c	ρ_h	ρ_l	P_{co}
Coefficient	0.610864	0.721895	0.750183	0.647782	0.6267

The results in table 4.1 provide support for the graphical representation in Figure 4.2. The fairly strong positive correlation indicates that the two volatility series move together over time although does not indicate the direction of causation.

4.3.3 OLS Regression Analysis and Unit Root Tests

To further examine the relationship the following OLS regression was also run, again using daily opening, closing, high and low values:

$$VFTSE_t = a + bVIX_t + e_t \tag{4.2a}$$

In addition, the following OLS regression was run for VIX closing on VFTSE opening:

$$VFTSE_{ot} = a + bVIX_{ct-1} + e_t \tag{4.2b}$$

Table 4.2: OLS Regression Results for Equation 4.2

	Coefficient	Standard Error	t- statistic (p)	R^2
Opening	0.506943	0.037696	13.47453 (8.67E-33)	0.373154
Closing	0.494773	0.027158	18.21865 (1.08E-50)	0.521132
High	0.511366	0.025809	19.81366 (9.79E-57)	0.5627755
Low	0.469756	0.031634	14.84989 (6.49E-38)	0.419622
Closing on Opening	0.522492	0.037262	14.02211(0.0000)	0.392752

The results presented in Table 4.2 indicate a positive and significant relationship between the two series. However care must be taken to examine for a unit root in each series in order to guard against spurious interpretation of the regression results. Hence it was proposed that the following augmented Dickey-Fuller test, with a null hypothesis of a unit root, was performed on each series:

$$\Delta y_t = \psi y_{t-1} + \sum_{i=1}^{p} \alpha_i \Delta y_{t-i} + u_t \tag{4.3}$$

Where y_t relates to each individual series for the VIX and VFTSE. The test is initially performed without a time trend as we would not expect to find a deterministic trend in a volatility index. However for completeness the test was subsequently run with the inclusion of a time trend.

The running of a Breusch-Godfrey LM test confirmed the presence of serial correlation in the VIX and in the VFTSE. An Augmented Dickey-Fuller test with a maximum of 2 lags of the dependent variable was found to be appropriate. 3 lags of the dependent variable were required to remove the serial correlation in VFTSE opening values when a deterministic trend is included. The results are presented in Tables 4.3(a) and 4.3(b). Subscripts o, c, h and l are used to denote opening closing, high and low values respectively.

Table 4.3 (a) Augmented Dickey-Fuller Test Results (Constant)

	DF t-Statistic	Prob	Unit Root	Lags	DF t-statistic 1^{st} Diff
VIX_o	-3.117215*	0.0263	Y	2	-18.45321
VIX_c	-3.358579**	0.0132	Y	2	-18.24469
VIX_h	-3.189547**	0.0216	Y	2	-16.40145
VIX_l	-2.915457*	0.0447	Y	2	-17.82849
$VFTSE_o$	-3.555261	0.0073	N	1	-15.53693
$VFTSE_c$	-3.173655*	0.0225	Y	1	-16.80101
$VFTSE_h$	-3.170122*	0.0228	Y	1	-17.23061
$VFTSE_l$	-4.137819	0.0010	N	2	-23.27591

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

Table 4.3 (b) Augmented Dickey-Fuller Test Results (Constant & trend)

	DF t-Statistic	Prob	Unit Root	Lags	DF t-statistic 1^{st} Diff
VIX_o	-3.248282*	0.0771	Y	2	-18.42716
VIX_c	-3.521989**	0.0388	Y	2	-18.22055
VIX_h	-3.344442*	0.0612	Y	2	-16.37877
VIX_l	-3.067644***	0.1160	Y	2	-17.80482
$VFTSE_o$	-3.854432*	0.0151	Y	3	-15.51366
$VFTSE_c$	-3.361460**	0.0586	Y	1	-16.77698
$VFTSE_h$	-3.333089**	0.0629	Y	1	-17.20848
$VFTSE_l$	-4.304823	0.0035	N	1	-23.23913

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

In the levels, for the majority of cases, the test statistic does not exceed the critical value at least at the 10% level. Therefore the null hypothesis of a unit root in the volatility series cannot be rejected. All series are found to be difference stationary. Hence all series except for $VFTSE_O$ and $VFTSE_L$ are integrated of order 1 or I(1). The results are largely insensitive to the inclusion of the trend term other than $VFTSE_O$ which is found to contain a unit root when the trend is included.

4.3.4 Granger Causality Tests

Granger (1969) pioneered the analysis of causality in financial data. In order to establish the likelihood of any temporal directional effects Granger Causality tests are performed. This involves testing whether past values of variable ‘x’ are able to significantly explain current values of variable ‘y’ once past values of ‘y’ have been controlled for. If this is found to be the case then ‘x’ can be said to Granger cause ‘y’. The same test can then be repeated to establish whether ‘y’ Granger Causes ‘x’. The first-differenced or returns series must be used because an assumption in Granger Causality is that the series under consideration are stationary. Granger Causality is also based on the fundamental assumption that the past can predict the future but the future cannot predict the past. Tests of causality in the context of this study are used to further establish the relationship between the VIX and VFTSE and hence add weight to the justification for using the former as a proxy for the latter.

Table 4.4 contains the results of Granger Causality tests using four lags, with optimal lag length selected using the akaike information criterion. The F-statistics are reported for each direction. Figures in parentheses are probability values.

Table 4.4: Granger Causality Tests of the Relationship between the VIX and the VFTSE Volatility Indexes

US indicates the first difference of the VIX and UK indicates the first difference of the VFTSE.

Direction	US → UK	UK → US
Opening	3.88710 (0.00430)***	2.73896 (0.02900)**
Closing	8.92138 (8.2E-07)***	3.04702 (0.01749)**
High	18.8761 (8.0E-14)***	4.85753 (0.00083)***
Low	8.19787 (2.8E-06)***	1.78305 (0.13220)
Closing on Opening	5.74277 (0.0002)***	2.84356 (0.0244)

***significant at the 1% level, **significant at the 5% level. Figures in parentheses are p-values.

The preliminary results in table 4.4 indicate that there are relationships between the VIX and the VFTSE. For all pairs of variables UK implied volatility appears to react significantly to US implied volatility. Furthermore, for the opening and closing pairs, US implied volatility appears to react significantly to UK implied volatility. Most importantly, opening UK implied volatility reacts significantly to closing US implied volatility. These results should be interpreted with caution however because they are sensitive to the choice of lag length. In addition, a finding that ‘x’ does not Granger Cause ‘y’ does not necessarily imply that ‘x’ and ‘y’ are independent.

4.3.5 Cointegration Tests

Given that pairs of closing and high values including a constant and pairs of opening, closing and high values including a constant and trend are non-stationary in the levels but stationary in first-differences, it would seem reasonable to proceed with cointegration tests on these variables. Results are presented for all pairs for completeness. Where two series are integrated of order one [I(1)], it may be possible to combine these series to produce a series with a lower order of integration. In other words, this method is used to establish if the series are cointegrated. The finding of cointegration indicates a stable long-run equilibrium relationship between the two series.

The Engle and Granger (1987) procedure is employed which first involves running the following cointegrating regressions for the respective pairs of series:

$$VFTSE_t = \alpha + \beta VIX_t + e_t \quad (4.4a)$$

$$VFTSE_{o_t} = \alpha + \beta VIX_{c_{t-1}} + e_t \quad (4.4b)$$

The regression is underpinned by an assumption that the direction of causation is from the US to the UK. This seems to be a reasonable assumption given the strength of the Granger Causality results. The residuals produced from the regression will correspond to the error in equilibrium. These residuals are then tested for a unit root using an ADF test. If it is inferred that the residuals do not contain a unit root and hence the error term is stationary, then the null hypothesis that the two difference series are not cointegrated will be rejected. This then permits inference that there is a meaningful relationship between the series.

Table 4.5 Results of Engle Granger Cointegration Tests

	Constant		Constant & Trend	
	τ-statistic	**Probability**	**τ-statistic**	**Probability**
Opening	-5.600462	0.0000	-5.816573	0.0000
Closing	-5.5992663	0.0000	-6.10042	0.0000
High	-6.074444	0.0000	-6.129917	0.0000
Low	-6.370623	0.0000	-6.436467	0.0000
Closing on Opening	-6.454672	0.0000	-6.651217	0.0000

For tests with a constant and constant with a trend the MacKinnon (1991) 5% critical values are -2.870899 and -3.424775 respectively.

Table 4.5 compares the computed τ-statistic with the appropriate critical values. It is clear that none of the series of residuals contains a unit root. As a it can be inferred that all of the series are stationary. Furthermore, given the unit root test results reported in tables 4.3 (a) and 4.3 (b) it can also be inferred that cointegration exists between the pairs of closing and high values including a constant and pairs of opening, closing, high and closing on opening values including a constant and trend.

4.3.6 Conclusion

The results presented in the previous sections indicate that a stable, long-run relationship between the VIX and the VFTSE exists. This is helpful given the lack of a UK-based aggregate market volatility index throughout much of the period under investigation. Whilst accepting that this is not an ideal solution it is justifiable to proceed by using the lagged VIX as a proxy for UK implied volatility and, by extension, sentiment of investors in the UK options market.

4.4 The VIX and the UK Equity Market in the Pre-Financial Crisis, Crisis and Post-Crisis Periods

4.4.1 Introduction

The last 30 years have been characterised by significant globalisation of financial markets with a consequent increase in the risk of contagion when crises occur. A particularly strong link exists between the markets of the US and the UK. Hence there is justification for using investor sentiment in the US to proxy for that in the UK; this is further supported by the results in the preceding section. The analysis that follows comes with that these markets are not perfectly positively correlated. However the correlation between opening UK volatility on day t and US volatility

The sample period to be examined is from June 2006 through December 2010 so as to include one year of data from prior to the onset of the crisis. Sub-periods are defined as the pre-crisis period, crisis period and the post-crisis period. The beginning of the pre-crisis period is initially chosen as January 2007. However, as this choice is rather arbitrary a number of alternative pre-crisis periods will also be analysed. The crisis period is selected to begin in June 2007 and continue until the end of December 2008. The remainder of the sample is defined as the post-crisis period. The purpose of sub-dividing the periods is to analyse the evolution of investor sentiment as the crisis itself evolved through a number of distinct phases.

4.4.2 Data

FTSE100 index data and dividend yields are collected from Datastream and used to construct a daily returns series. Daily VIX data is collected from the CBOE. Closing values are selected as the appropriate series for this analysis. Closing values are constructed from recently traded contracts and less likely than opening prices to contain stale information. Given the 6 hour time difference between the US (Central Time) and UK markets, closing VIX values are also considered. However, these are not considered useful in the tests and do not provide any additional information to that presented in the results tabulated in the following sections. Daily highs and lows are not considered as they are extremes and have a high probability of being outliers. Summary statistics for the variables employed are presented in table 4.6.

Table 4.6 Summary Statistics for the VIX and FTSE100

1st June 2006 – 31st December 2010

Variable	Mean	Standard Deviation	Skewness	Kurtosis	ρ_1	ρ_2	ρ_3	ρ_4
VIX	0.244158	0.119652	1.742722	6.600652	0.981	0.968	0.959	0.949
ΔVIX	0.000174	0.071597	0.595201	7.302882	-0.126	-0.089	0.015	-0.035
RFTSE	0.000123	0.015085	-0.034797	9.679117	-0.059	-0.084	-0.059	0.111
DEVMA	-1.70E-05	0.013468	0.737808	11.53771	-0.075	-0.144	-0.186	-0.071

VIX is the S&P 500 volatility index

RFTSE are daily returns on the FTSE100 index

DEVMA is the percentage deviation of the FTSE100 from its 5-day moving average

$\rho_1 - \rho_4$ are the first four autocorrelations

The mean level of the VIX during the sample period is 24.42% whilst its first difference has a mean of 0.0174%. The mean daily returns on the FTSE100 are 0.0123% whilst the mean deviation of the FTSE100 from its 5-day moving average is -0.000017%.

Autocorrelation is present for the VIX and for the deviation of the FTSE100 from its 5-day moving average. Autocorrelation is present but less strong for the first difference of the VIX and for the FTSE100 returns. These results are fairly unsurprising; in particular we would expect volatility indexes to be autocorrelated as volatility is typically characterised by clustering. The high levels of skewness and kurtosis indicate non-normality and provide further support for the presence of autocorrelation and heteroskedasticity. Appropriate adjustments will therefore be made in the empirical tests. The models to be estimated will focus on three key issues. It is important to establish how the VIX responds to positive and negative FTSE returns and deviations from its 5-day moving average in order to assess whether it acts as a fear gauge[22] for the UK market. Lagged VIX returns are also included as an explanatory variable and the model is run for the entire sample period, the pre-crisis period, crisis period and post-crisis period. Secondly, the predictive power of the VIX for actual volatility in the UK will be analysed and compared to that of time-varying volatility models such as GARCH and EWMA. Finally tests will be constructed to examine the impact of the lagged VIX on aggregate UK stock market returns in the pre-crisis period and the immediate aftermath. The pre-crisis period is defined as above although a shorter crisis period will be examined for the remainder of 2007.

4.4.3 Methodology

The initial step is to establish the relationship between aggregate market returns and implied volatility by running regression 4.5. It is hypothesised that the opposite response of the VIX to negative and positive returns on the S&P 500 similar to those

[22] Whaley (2000) coined the term 'investor fear gauge' in response to the observation that high levels of market turmoil coincided with high levels of the VIX. The key relationship is that when the market falls the VIX rises and vice versa.

identified by Fleming, Ostdiek and Whaley (1995) will also be present in the FTSE100. Variables to capture the effect of positive and negative deviations of the FTSE100 from its 5-day moving average are also included. Simon (2003) notes that this specification allows the impact of spot returns on the volatility index to vary according to perceived trends. The model will therefore include four dummy variables to allow for negative and positive returns and deviations from the moving average. The lagged value of the VIX is included to capture any mean reversion. The following model is estimated using the Newey and West (1987) method that corrects for the presence of both heteroskedasticity and autocorrelation:

$$\Delta VIX_t = \propto + \beta_1 VIX_{t-1} + \beta_2 D_1 RFTSE_t^+ + \beta_3 D_2 RFTSE_t^- + \beta_4 D_3 DEVMA_t^+ + \beta_5 D_4 DEVMA_t^- + \varepsilon_t \quad (4.5)$$

A second set of regressions, given by equations (4.6a) and (4.6b) are run to test for any response of the FTSE100 to the levels and changes in the VIX in the entire sample period. A shorter sample period is employed and is divided into three sub-periods. The pre-crisis period is selected as 3rd January to 31st May 2007, the crisis period as 1st June 2007 to 31st December 2008 and the post-crisis period as 2nd January 2009 to 31st December 2010. Returns on the FTSE100 will be regressed on contemporaneous levels and first-differences of the VIX. Lagged FTSE100 returns are included as a control variable for market-wide effects.

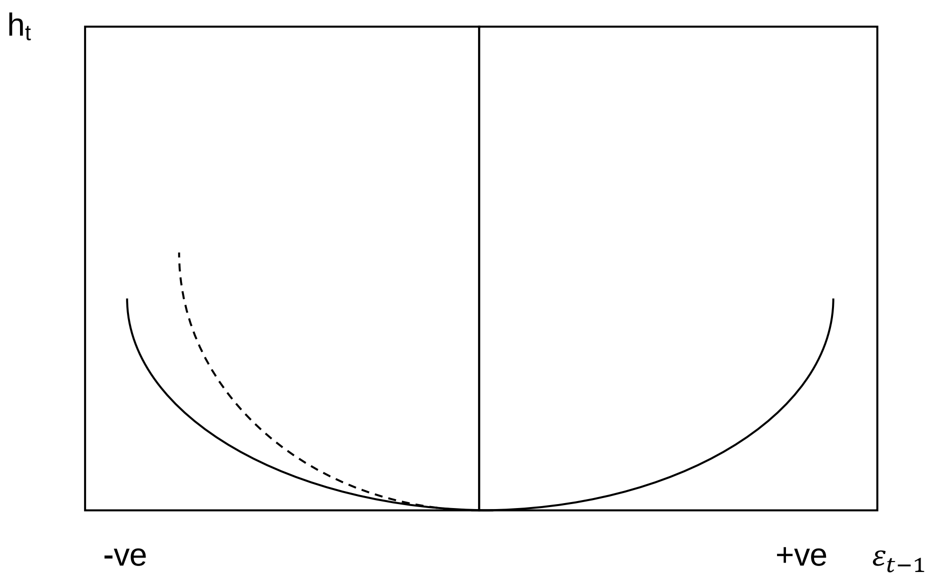
$$RFTSE_t = \propto + \beta_1 RFTSE_{t-1} + \beta_2 VIX_t + \varepsilon_t \quad (4.6a)$$

$$RFTSE_t = \propto + \beta_1 RFTSE_{t-1} + \beta_2 \Delta VIX_t + \varepsilon_t \quad (4.6b)$$

Following the literature reviewed in section 4.2 an important section of this study involves an analysis of the power of the VIX to predict actual volatility in the UK market. A direct measure of the information content of option prices is the ability of implied volatility to predict the future volatility of the underlying asset. Implied volatility predictions will be compared with those produced by a GJR GARCH (Glosten, Jaganathan and Runkle, 1993) model and an EWMA model. The use of a GJR GARCH model is consistent with previous studies, such as Simon (2003), as it picks up the frequently observed asymmetry in financial time series data. The value of λ is chosen as 0.94 which is the appropriate value for daily index volatilities as suggested by J.P. Morgan's RiskMetrics in 1994.

The GJR GARCH is designed to capture the asymmetric response of volatility to news. In short, it is a typical characteristic of financial time series data that it becomes more volatile in response to bad news than in response to good news of equivalent magnitude. A standard GARCH (p,q) model does not capture this 'stylised fact'. The asymmetric response can be illustrated in the following news impact curve of the type proposed by Engle and Ng (1993):

Figure 4.3 GARCH News Impact Curves



The solid line represents the GARCH(1,1) whilst the dashed line represents the GJR GARCH which dominates on the negative side of the diagram.

Initially the GJR GARCH model will be estimated in order to determine whether the FTSE100 displays an asymmetric response of volatility to news. The model is presented in equations (4.7a) and (4.7b):

$$R_t = \mu + \varepsilon_t, \ \varepsilon_t \sim N(0, h_t) \qquad (4.7a)$$

$$h_t = \omega + \alpha\varepsilon_{t-1} + \phi\varepsilon_{t-1}D_{t-1} + \beta h_{t-1} \qquad (4.7b)$$

Where:

$R_t = ln(P_t/P_{t-1})$

P_t = value of the FTSE100 index on day t

$D_{t-1} = 0$ *if* $\varepsilon_{t-1} > 0$, *or* $D_{t-1} = 1$ otherwise

Hence the dummy variable magnifies the impact of the lagged innovation if it is negative but the model collapses to a GARCH (1,1) if the lagged innovation is positive. Hence this specification is capable of capturing the asymmetric response of volatility to news. If ϕ is found to be statistically significant and positive then it can be inferred that negative return innovations have a greater impact on the conditional volatility of the FTSE100 than positive return innovations of the same magnitude. Once more, predicted volatility will be analysed over the pre-crisis, crisis and post-crisis periods as well as over the entire sample period.

Predictive Power of the VIX, GARCH and EWMA Forecasts for FTSE100 Volatility

In order to test the forecasting performance of the VIX it is compared to an out-of-sample GJR GARCH over the period January 2007 to December 2010. As the model is formulated to forecast one day ahead, a method similar to that of Lamoureux and Lastrapes (1993) is adopted to transform GJR GARCH forecasts of daily variance to forecasts of average daily variance for the remaining life of the relevant option contract. The asymmetric GARCH parameters are estimated from FTSE100 returns over the two year period which immediately precedes the forecasting period. An out-of-sample model is used to produce estimates of volatility for day t+1 and is rolled over for each subsequent day to produce a series of estimates up to day n where n is one week prior to the maturity of the option. The average of these volatility estimates is taken as the market consensus of volatility for the period under consideration.

Finally the forecasting power of the VIX and GJR GARCH is compared with that of the following EWMA model with λ set equal to 0.94:

$$\sigma_t^2 = \lambda\sigma_{t-1}^2 + (1-\lambda)\varepsilon_{t-1}^2 \qquad (4.8)$$

The remaining analysis in this section involves an adaptation of the methodology set out in Simon (2003). In order to establish whether the VIX has predictive power in relation to UK aggregate market return volatility a number of regressions are run using levels and first differences. The predictive power of the VIX is compared to that of the GARCH and EWMA models. The first of these regressions are in the levels and are given by equation (4.9).

$$\sigma_{t,T} = \alpha + \beta\sigma_t^{VIX,G,EWMA} + \varepsilon_{t,T} \tag{4.9}$$

Where,

$\sigma_{t,}$ = the actual volatility of FTSE100 returns from 22 trading days before the nearest to maturity option expiration through expiration.

σ^{VIX}, σ^{G}, σ^{EWMA} = VIX, GARCH and EWMA forecasts of actual volatility measured 22 trading days prior to expiration of the nearest to maturity option.

The regression model in first differences is given by equation (4.10).

$$\sigma_{t,T} - \sigma_{t-1,T-1} = \alpha + \beta\left[\sigma_t^{VIX,G,EWMA} - \sigma_{t-1,T-1}\right] + \varepsilon_{t,T} \tag{4.10}$$

In equation 4.10 the dependent variable is the change in actual FTSE100 volatility over the 22 days prior to the previous option expiration to the 22 days prior to the nearest to maturity option expiration. The explanatory variable is the change in actual volatility predicted by the VIX, GARCH or EWMA from its level prior to the previous option expiration.

Consistent with Blair, Poon and Taylor (2001), Giot (2005) and Frijns, Tallau and Tourani-Rad (2010) the actual or realised volatility is computed as the sum of the squared daily returns. This is presented in equation (4.11):

$$\sigma_{k,t} = \sqrt{\textstyle\sum_{j=1}^{k} r_{t+j}^2} \tag{4.11}$$

Each model will indicate whether or not the volatility forecasts are biased. For an unbiased forecast, the value of α should not be significantly different to zero and the slope coefficients should not be significantly different to one. For a volatility forecast to have predictive power the coefficients attached to the volatility forecast in each regression should be significantly greater than zero. In addition, Wald tests are performed to test the joint restrictions that each intercept is equal to zero and that the coefficient attached to each of the volatility forecasts is equal to one.

A further set of regressions is run in levels and first differences to establish whether the information provided by the GARCH or EWMA forecasts is included in the VIX. Equations (4.12a) for the levels and (4.12b) for first differences represent the regression of actual FTSE100 volatility on the VIX and either the GARCH or the EWMA volatility forecasts.

$$\sigma_{t,T} = \alpha + \beta\sigma_t^{VIX} + \gamma\sigma_t^{G,EWMA} + \epsilon_{t,T} \tag{4.12a}$$

$$\sigma_{t,T} - \sigma_{t-1,T-1} = \alpha + \beta\left[\sigma_t^{VIX} - \sigma_{t-1,T-1}\right] + \gamma\left[\sigma_t^{G,\ EWMA} - \sigma_{t-1,T-1}\right] + \varepsilon_{t,T} \tag{4.12b}$$

If the information provided by the GARCH and EWMA volatility forecasts is contained in the VIX then the coefficients attached to these forecasts should not be statistically significant whilst the coefficients attached to the VIX should be statistically significant. Likewise if information provided by the VIX is contained in the GARCH and EWMA forecasts then the coefficients attached to the VIX will not be statistically significant.

Predictive Power of the VIX for FTSE 100 Returns

A further test is run to investigate whether the VIX has any predictive power for FTSE100 returns. If lagged values of the VIX, in levels or returns, are negatively and significantly related to FTSE100 returns then the inference may be drawn that, if investor expectations are incorporated into implied volatility, options markets have predictive power for equity market returns. The regressions given by equations (4.13a) and (4.13b) will be used to test this proposition.

$$RFTSE_t = a + b_1 RFTSE_{t-1} + b_2 VIX_{t-n} + e_t \qquad (4.13a)$$

$$RFTSE_t = a + b_1 RFTSE_{t-1} + b_2 \Delta VIX_{t-n} + e_t \qquad (4.13b)$$

The equation is specified for 22 lags although models with 1, 7 and 14 day lags will also be analysed. The selection of lags is important as 22 working days is consistent with the forward-looking horizon of implied volatility. The 1-day lag test examines for the presence of price discovery with intermediate lags examined for completeness.

4.4.4 Results

The results from regression 4.5 are presented in table 4.7

Table 4.7 Model of daily changes in the VIX

$$\Delta \boldsymbol{VIX_t} = \propto + \boldsymbol{\beta_1 VIX_{t-1}} + \boldsymbol{\beta_2 D_1 RFTSE_t^+} + \boldsymbol{\beta_3 D_2 RFTSE_t^-} + \boldsymbol{\beta_4 D_3 DEVMA_t^+} + \boldsymbol{\beta_5 D_4 DEVMA_t^-} + \boldsymbol{\varepsilon_t}$$

Variable	Whole Period	Pre-Crisis	Crisis	Post-Crisis
A	-0.012512*** (0.0062)	0.183901*** (0.0074)	0.014446* (0.0691)	0.026154*** (0.0042)
β_1	-0.101582*** (0.0000)	-1.541497*** (0.0085)	-0.096575*** (0.0015)	-0.169199*** (0.0000)
β_2	-1.214738*** (0.0002)	-1.695082 (0.3686)	-0.943129** (0.0123)	-1.227084** (0.0278)
β_3	-3.592918*** (0.0000)	-5.534605 (0.2634)	-3.293195*** (0.0000)	-4.042293*** (0.0000)
β_4	0.942115 (0.1131)	0.816662 (0.7880)	0.894682 (0.3192)	1.494741* (0.0693)
β_5	1.677950 (0.4793)	-5.846116 (0.3970)	1.308756 (0.2740)	-1.130183 (0.4550)
R^2	0.267450	0.258229	0.283649	0.327680

Figures in parentheses are p-values. *** significant at the 1% level; ** significant at the 5% level, * significant at the 10% level.

It is apparent that for the whole sample period and each sub-period that the VIX displays mean-reversion as each value of β_1 is negative. Each coefficient estimate on the lagged VIX return is negative and significant. Therefore a higher level of the VIX is associated with a subsequent decline and vice versa. The coefficients on the negative and positive lagged FTSE100 returns are also negative and significant, except for during the pre-crisis period, indicating that positive lagged returns on the FTSE100 are associated with declines in the VIX whilst negative lagged FTSE100 returns are associated with increases in the VIX. However these results should be interpreted with caution because if, as expected, the VIX is moving in the opposite direction to the US aggregate market then what is observed here could merely be a result of correlation between the US and UK large capitalisation stock markets. It is also important to note that the 'contemporaneous' values for the VIX are also lagged by six hours given the time difference between London and Chicago. Coefficients attached to deviations of the FTSE100 from its 5-day moving average are not statistically significant in both the whole period and each sub-period other than for positive deviations in the post-crisis period, hence no inferences can be drawn about these. The main conclusion to draw from this analysis is that the VIX moves in opposite directions relative to the UK large capitalisation stock market. However the primary relationship is with the US equity market. It follows that the evidence supporting the notion of the VIX as a proxy fear gauge for the UK market is relatively weak. Given the relationship between the UK and US equity markets it is unsurprising that a highly directional relationship is identified.

Table 4.8 FTSE100 Returns and the VIX Levels and First-Differences

Levels	$RFTSE_t = \propto + \beta_1 RFTSE_{t-1} + \beta_2 VIX_{t-1} + \varepsilon_t$			
Variable	**Whole Period**	**Pre-Crisis**	**Crisis**	**Post-Crisis**
A	0.003804*** (0.0065)	0.012498** (0.0206)	0.003412 (0.2038)	0.006613*** (0.0045)
β_1	-0.070820** (0.0448)	-0.026112 (0.7982)	-0.100271* (0.0651)	-0.027755 (0.4809)
β_2	-0.015034** (0.0221)	-0.092191** (0.0398)	-0.015534 (0.1690)	-0.021921** (0.0213)
R^2	0.017561	0.062568	0.020576	0.020871
First-Differences	$RFTSE_t = \propto + \beta_1 RFTSE_{t-1} + \beta_2 \Delta VIX_t + \varepsilon_t$			
Variable	**Whole Period**	**Pre-Crisis**	**Crisis**	**Post-Crisis**
A	0.000144 (0.6392)	0.000691 (0.2119)	-0.000593 (0.3399)	0.000507 (0.2686)
β_1	-0.023848 (0.3786)	0.064261 (0.6450)	-0.035573 (0.3479)	-0.006917 (0.8693)
β_2	-0.101020*** (0.0000)	-0.036333*** (0.0000)	-0.119779*** (0.0000)	-0.104705*** (0.0000)
R^2	0.232138	0.146296	0.237117	0.272819

*** significant at the 1% level; ** significant at the 5% level, * significant at the 10% level. Figures in parentheses are p-values.

The most striking feature of the results in table 4.8 is the significant inverse relationship between the first-difference of the VIX and the FTSE100. The VIX in the level is less important as the VIX is non-stationary hence results are likely to be misleading. The first-difference results suggest that the VIX is a useful indicator of investor sentiment in the UK market. When investors are concerned in times of falling returns the VIX rises; hence the VIX lives up to its reputation as a fear index. This is particularly apparent when the model is run in first-differences and produces coefficients that are all negative and significant. The negative coefficient attached to the lagged VIX indicates that increasing volatility is associated with a subsequent fall in returns. The results are consistent by sub-period except for the crisis period in the levels.

Table 4.9 Asymmetric GARCH Model of Daily FTSE100 Returns

$$R_t = \mu + \varepsilon_t\,,\ \varepsilon_t \sim N(0, h_t)$$

$$h_t = \omega + \alpha\varepsilon_{t-1} + \phi\varepsilon_{t-1}D_{t-1} + \beta h_{t-1}$$

	ω	α	Φ	β
Period				
Entire	0.0000028*** (0.0000)	-0.013927 (0.3411)	0.188046*** (0.0000)	0.904380*** (0.0000)
Pre-Crisis	0.00000397*** (0.0000)	-0.233824*** (0.0000)	0.298379*** (0.0000)	1.00584*** (0.0000)
Crisis	0.0000102*** (0.0001)	-0.053287** (0.0291)	0.323583*** (0.0000)	0.870266*** (0.0000)
Post-Crisis	0.00000328*** (0.0020)	-0.030228 (0.1278)	0.162253*** (0.0000)	0.924778*** (0.0000)

Figures in parentheses are p-values. ***Significant at the 1% level **Significant at the 5% level

The results displayed in Table 4.9 provide support for the notion of asymmetric volatility in response to innovations of equivalent magnitude but opposite sign. The significant and positive value of ϕ for the entire period indicates that the news effect is asymmetric. Notably the news effect is most prominent in the crisis and pre-crisis periods. In particular, during the crisis period, negative innovations result in considerable increases in conditional volatility. The value of α is insignificant in the pre-crisis and crisis periods, however if the model is run as a standard GARCH (1,1) the influence of the lagged innovation becomes significant. The results also indicate that conditional volatility is mean-reverting for all periods.

Tables 4.10 and 4.11 contain the regression results from equations (4.9) and (4.10) and is based on 47 observations over the period from January 2007 to December 2010.

Table 4.10 The Predictive Power of Volatility Forecasts (Levels)

$$\sigma_{t,T} = \alpha + \beta\sigma_t^{VIX,G,EWMA} + \varepsilon_{t,T}$$

Constant	VIX	GARCH	EWMA	R^2	D-W	Wald Test
-0.002877** [0.001107]	0.516515*! [0.089009]			0.275057	1.35	56.937 (0.0000)
-0.003512** [0.001599]		0.724681*! [0.184368]		0.426721	1.93	79.02 (0.0000)
-0.002531** [0.001208]			0.572193*! [0.120957]	0.273363	1.62	41.358 (0.0000)
-0.003117** [0.001205]	-0.088156 [0.284704]	0.808352*** [0.435874]		0.429045	1.96	
-0.003009** [0.001152]	0.278611 [0.167417]		0.284019 [0.250889]	0.284056	1.49	

The Newey-West correction for autocorrelation and heteroskedasticity is used in the estimation and figures in parentheses are standard errors. * Significantly different from zero at the 10% level; ** at the 5% level. *** at the 1% level. The Wald test is for the joint hypothesis that the intercept is equal to zero and that the coefficient attached to the volatility estimate is equal to one. The Wald F-statistic is reported and probability values for the test are in parentheses. ! Significantly different from one.

The results presented in Table 4.10 indicate that the intercept coefficients in each case are significantly less than zero. Furthermore in all cases, except for that where GARCH and VIX volatility forecasts are jointly included in the model, the slope coefficients are significantly less than one indicating that the volatility forecasts are biased estimates of actual volatility. The results indicate that the VIX, GARCH and EWMA volatility forecasts all have significant forecasting power. The combination of a slope coefficient which is significantly greater than zero but significantly less than one and an intercept which is significantly less than zero indicates that when volatility forecasts are high relative to recent volatility their predictions of future volatility are too high. The VIX and EWMA forecasts each explain approximately 27% of the overall variation in the level of realised volatility whilst the GARCH forecast explains approximately 43%. The model estimated including the GARCH and VIX forecasts produces a GARCH coefficient which is not significantly different from one and an insignificant coefficient for the VIX. This suggests that the GARCH encompasses the forecasting information provided by the VIX. When the EWMA and VIX forecasts are included both slope coefficients become insignificant. Hence in all cases it is not possible to conclude that the information provided by the GARCH and EWMA volatility forecasts is contained in the VIX.

Table 4.11 The Predictive Power of Volatility Forecasts (First Differences)

$$\boldsymbol{\sigma_{t,T} - \sigma_{t-1,T-1} = \alpha + \beta\left[\sigma_t^{VIX,G,EWMA} - \sigma_{t-1,T-1}\right] + \varepsilon_{t,T}}$$

Constant	VIX	GARCH	EWMA	R^2	D-W	Wald Test
-0.003645 [0.005246]	0.335981! [0.403226]			0.046136	2.09	116.287 (0.0000)
-0.006446*** [0.002331]		0.919404*** [0.306324]		0.252161	2.19	25.435 (0.0000)
-0.003400 [0.007766]			0.39409! [0.799395]	0.026736	2.25	61.953 (0.0000)
-0.005879 [0.004270]	-0.083846 [0.361270]	0.969166*** [0.344148]		0.254296	2.25	
-0.003535 [0.007878]	0.354077** [164455]		-0.035416 [0.863421]	0.046218	2.09	

The White correction for heteroskedasticity is used in the estimation and figures in parentheses are standard errors. * Significantly different from zero at the 10% level; ** at the 5% level. *** at the 1% level. The Wald test is for the joint hypothesis that the intercept is equal to zero and that the coefficient attached to the volatility estimate is equal to one. The Wald F-statistic is reported and probability values for the test are in parentheses. ! Significantly different from one.

The results in Table 4.11 show that the GARCH forecast by itself has a significantly positive coefficient which is not significantly different from one, however the intercept is significantly negative. Hence the GARCH forecast produces biased predictions of actual volatility changes. When GARCH estimates are high relative to recent realised volatility they over-predict rising volatility. The GARCH forecast explains approximately 25% of the overall variation in realised volatility changes but the coefficients attached to the VIX and EWMA forecasts are not significantly different to zero.

When both the GARCH and VIX forecasts are included in the model the GARCH continues to enter with a significantly positive coefficient whilst the VIX remains insignificant. Hence the overall results are unchanged. Interestingly when the EWMA and VIX are included the VIX volatility forecast becomes significantly greater than zero although it only explains approximately 4.6% of the overall variation in realised volatility changes.

Overall these results suggest that the GARCH model provides the most powerful prediction of realised volatility. It provides significant predictive power both in levels and first differences although the results also indicate that GARCH gives a biased forecast of realised volatility. Furthermore, although significant in the levels, the forecasting power of the EWMA and VIX is considerably weaker and insignificant when combined with GARCH and in first-differences.

The VIX and FTSE100 Return Predictability

Potential return predictability is examined using equations (4.13a) and (4.13b) for a variety of lag lengths denoted by the letter n. Results are presented in tables 4.12, 4.13 and 4.14.

Table 4.12 Predictive Power of the Lagged VIX for FTSE100 Returns: 2006-2010

$$RFTSE_t = a + b_1 RFTSE_{t-1} + b_2 VIX_{t-n} + e_t$$

$$RFTSE_t = a + b_1 RFTSE_{t-1} + b_2 \Delta VIX_{t-n} + e_t$$

Constant	RFTSE(-1)	VIX(-1)	DVIX(-1)	VIX(-22)	DVIX(-22)	R^2
0.000159 (0.6830)	-0.200042*** (0.0000)		-0.061705*** (0.0000)			0.069394
0.000644 (0.6072)	-0.060943* (0.0714)	-0.002101 (0.7225)				0.003761
0.000116 (0.7972)	-0.058251* (0.0501)				0.005804 (0.3533)	0.004085
-0.000235 (0.8400)	-0.057871 (0.2542)			0.001440 (0.7842)		0.003456

*Significant at the 10% level, ** at the 5% level, *** at the 1% level. Figures in parentheses are p-values.

The results in table 4.12 indicate that values of the VIX lagged by 22 days have no significant explanatory power for FTSE100 returns for the full period between 2006 and 2010. However a negative and significant relationship was evident when VIX returns lagged by 1 day were used. Table 4.13 illustrates that similar results were produced when the sample was restricted to the pre-crisis period from the beginning of January to the end of June 2007.

Table 4.13 Predictive Power of the Lagged VIX for FTSE100 Returns: Pre-Crisis Period January-June 2007

$$RFTSE_t = a + b_1 RFTSE_{t-1} + b_2 VIX_{t-n} + e_t$$

$$RFTSE_t = a + b_1 RFTSE_{t-1} + b_2 \Delta VIX_{t-n} + e_t$$

Constant	RFTSE(-1)	VIX(-1)	DVIX(-1)	VIX(-22)	DVIX(-22)	R^2
0.002507 (0.5770)	0.007285 (0.9469	-0.014272 (0.7071)				0.001736
0.000851 (0.1680)	-0.156268 (0.2116)		-0.042976*** (0.0017)			0.178380
-0.004160 (0.2824)	0.056572 (0.6765)			0.037500 (0.1977)		0.013693
0.000504 (0.4692)	0.067728 (0.6241)				0.005306 (0.5564)	0.006306

*Significant at the 10% level, ** at the 5% level, *** at the 1% level. Figures in parentheses are p-values.

The model was also run with the VIX in the levels and first-differences with lags of seven and fourteen days however no significant explanatory power was found.

A much shorter pre-crisis period which consisted of the 30 days prior to July 2007 was also examined. Again the results failed to provide significant evidence of return predictability other than for the VIX lagged by seven days. Hence this result is presented in Table 4.14 for completeness.

Table 4.14 Predictive Power of the Lagged VIX for FTSE100 Returns: Short Pre-Crisis Period May/June 2007

$$RFTSE_t = a + b_1 RFTSE_{t-1} + b_2 VIX_{t-n} + e_t$$

$$RFTSE_t = a + b_1 RFTSE_{t-1} + b_2 \Delta VIX_{t-n} + e_t$$

Constant	RFTSE(-1)	VIX(-7)	DVIX(-7)	VIX	DVIX	R^2
0.025489* (0.0630)	0.261432 (0.1688)	-0.183032* (0.0543)				0.119175
0.000153 (0.9050)	0.151328 (0.4034)		0.014446 (0.4565)			0.061439
0.009010 (0.3522)	0.181844 ((0.3267)			-0.061028 (0.3554)		0.062242
0.000333 (0.7919)	0.203641 (0.2576)				-0.022339 (0.1562)	0.113471

*Significant at the 10% level, ** at the 5% level, *** at the 1% level. Figures in parentheses are p-values.

The weak results relating to lag lengths of greater than 1 day are likely to either be because investor sentiment captured by volatility indexes cannot be used as a predictor of aggregate market returns or, alternatively, the VIX is an inappropriate proxy for investor sentiment in the UK large capitalisation equity market. The significance of changes in the VIX lagged by 1 day indicate that there may be a mechanism for price discovery in option trading data which warrants further investigation.

4.4.5 Conclusion

The results presented in the preceding sections indicate that the VIX provides a useful indicator of investor sentiment. Despite representing implied volatility of S&P500 options, initial inspection appears to indicate that the VIX has some value as a proxy for investor sentiment in the UK aggregate large capitalisation stock market. Furthermore, the VIX appears to possess forecasting power for future realised FTSE100 return volatility. However, this finding should be interpreted with a considerable degree of caution because the forecasting power of the VIX disappears with the inclusion of conditional GARCH volatility in the model. This is unsurprising as the GARCH model produces estimates using UK data and also incorporates time-varying volatility. No significant predictive power of the VIX for FTSE100 returns is found. All of the results presented remain fairly consistent across the three sub-periods of the financial crisis. This indicates that there was no major change in the behaviour of options market traders as the crisis evolved. Or at least no major change in trader behaviour can be implied from this data set.

Both the VIX and the VFTSE demonstrate clear mean-reversion. Furthermore, as expected, there is a negative relationship between the VUK and the FTSE100 index. Implied volatility increases when the market falls and decreases when the market rises.

Given the results of the analysis of return predictability it would be inappropriate to draw any strong inferences regarding the relationship between the VIX and FTSE100 returns other than the VIX seems an inappropriate proxy for investor sentiment in the UK market for the period and sub-periods analysed. At best it indicates a weak price discovery mechanism. Consequently it is necessary to employ an alternative approach in the search for further insights.

4.5 The VUK and the UK Equity Market Before and During the Financial Crisis

4.5.1 Introduction

As a consequence of the (lack of) strength of the results in the previous section it is difficult to present a compelling argument for the relationship between the VIX and returns in the UK equity market. In order to further examine the relationship between implied volatility and spot asset returns, options market data will be used to construct an *ex ante* VFTSE which may be used to model the sentiment of investors in the UK prior to 2008. Henceforth this will be referred to as the VUK. The VUK will be constructed in a similar way to the VFTSE in order to be a consistent indicator of investor sentiment. This represents a unique contribution to the literature as it permits examination of a series which did not previously exist.

Areal (2008) examined three different methodologies to produce the VFTSE in order to find the preferred measure. Areal notes that the UK options market, although liquid, is not as liquid as that in the US. For example, most of the liquidity in the UK market is in close-to-the-money or at-the-money options. Hence it is inappropriate to construct a volatility index using an identical measure to that used to produce the VIX. As this study requires computation of an historical VUK index, an adaptation of Areal’s measure, which focuses on near-the-money options, will be employed.

4.5.2 Data

Data is collected to compute implied volatilities for the eight nearest-to-the-money option contracts. These options are two puts and two calls for the nearest to expiration and two puts and two calls for the second-nearest to expiration contracts.

Daily closing prices for FTSE100 European-style options, with their associated exercise prices, for close-to-the-money contracts with the nearest two maturity dates are collected from Euronext LIFFE. The entire sample period is from January 2006 to December 2010, a total of 1,232 observations. This is a longer period than that analysed in the previous section in order to compensate for the missing observations from the Euronext LIFFE data noted below. Consequently the previous computations on spot index data are repeated to ensure consistency. During the sample period the expiry date of options traded on LIFFE was the third Friday of the month or the previous working day if the Friday was a public holiday. The computations are performed excluding options with less than one week to maturity. This addresses the problems of low liquidity in close to expiration options and the high volatility associated with imminent exercise or expiry.

FTSE100 index closing prices and dividend yields are collected from Datastream for the entire sample period. There is no apparent consensus on the selection of an appropriate riskless rate of interest to include in the option pricing model. For example, Christensen and Prabhala (1998) assert that a one-month LIBOR rate should be used as the risk-free rate as this is the rate most likely to be faced by option traders. However numerous studies, including that of Areal (2008), suggest some matching of the interest rate to the maturity of the option. Daily UK Treasury-Bill rates for maturities closest to those of the options under consideration, collected from Datastream, are used for the purposes of this study as they facilitate a reasonable degree of maturity matching.

Table 4.15 Summary Statistics for the VUK and FTSE100

2nd January 2006 – 31st December 2012

Variable	Mean	Standard Deviation	Skewness	Kurtosis	ρ_1	ρ_2	ρ_3	ρ_4
VUK	0.188631	0.098100	2.054628	8.659449	0.953	0.922	0.904	0.892
ΔVUK	0.0000307	0.029821	-0.605756	21.13307	-0.167	-0.138	-0.076	0.029
RFTSE	0.0000494	0.014880	-0.060720	9.841489	-0.083	-0.050	-0.064	0.117
DEVMA	-0.0000119	0.013245	0.820014	11.39718	-0.097	-0.114	-0.188	-0.071

VUK is the FTSE100 volatility index

RFTSE are daily returns on the FTSE100 index

DEVMA is the percentage deviation of the FTSE100 from its 5-day moving average

$\rho_1 - \rho_4$ are the first four autocorrelations

The mean level of the VUK during the sample period is 18.86% whilst its first difference has a mean of 0.00307%. Hence the implied volatility extracted from FTSE 100 options in levels and first differences is considerably below that given by the VIX. This is to be expected given the relationship between the VIX and the VFTSE illustrated in Figure 4.2. Mean daily returns on the FTSE100 are 0.0049% and the mean deviation of the FTSE100 from its 5-day moving average is -0.0019%.

Autocorrelation is present for the VUK, first difference of the VUK, FTSE100 returns and the deviation of the FTSE100 from its 5-day moving average. Again these results are fairly unsurprising. The high levels of kurtosis provide further support for the presence of autocorrelation and heteroskedasticity. Appropriate adjustments will therefore be made in the empirical tests which will focus on the same key issues examined in section 4.4.

4.5.3 Methodology

The Black-Scholes-Merton model for options with a continuous dividend yield, as presented and explained in Chapter 3, is used to extract a series of implied volatilities for each of the option contracts in the sample. Implied volatilities are calculated by setting the Black-Scholes price equal to the market price for each option and solving for volatility for each of the 10,136 option prices in the sample.

The interpolation procedure presented in equation (4.14) is followed to produce at-the-money implied volatilities for nearest and second-nearest to expiration put and call options. This example uses notation for nearest to expiration puts.

$$\sigma_{p,N} = \sigma_{p,N}^{\frac{S_t}{K_t}<1} + \left(1 - \frac{S_t}{K_{t_{\frac{S_t}{K_t}<1}}}\right) X \frac{\left(\sigma_{p,N}^{\frac{S_t}{K_t}>1} - \sigma_{p,N}^{\frac{S_t}{K_t}<1}\right)}{\left(S_t/K_{t_{\frac{S_t}{K_t}>1}} - S_t/K_{t_{\frac{S_t}{K_t}<1}}\right)} \qquad (4.14)$$

Where:

S = price of the underlying asset

K = option exercise price

σ = implied volatility

The same procedure is applied to produce $\sigma_{p,S\text{-}N}$, $\sigma_{c,N}$ and $\sigma_{c,S\text{-}N}$.

The implied volatility for the nearest and second nearest to expiration contracts is then computed by averaging that of the corresponding puts and calls as illustrated in equations (4.15a) and (4.15b).

$$\sigma_N = \left(\sigma_{c,N} + \sigma_{p.N}\right)/2 \qquad (4.15a)$$

$$\sigma_{SN} = \left(\sigma_{c,SN} + \sigma_{p.SN}\right)/2 \qquad (4.15b)$$

A further interpolation will be performed on σ_N and $\sigma_{S\text{-}N}$ to produce a time series of 30 calendar day (or 22 trading day) to maturity at-the-money implied volatilities which is our VUK index. This interpolation is given in equation (4.16).

$$VUK = \sigma_{N_t} + \left(\frac{30 - N_t}{SN_t - N_t}\right) x\, ABS(\sigma_{SN_t} - \sigma_{N_t}) \qquad (4.16)$$

An initial inspection of the VUK alongside FTSE100 returns is presented in Figure 4.4.

Figure 4.4 FTSE100 Daily Returns and the VUK: 2006-2010

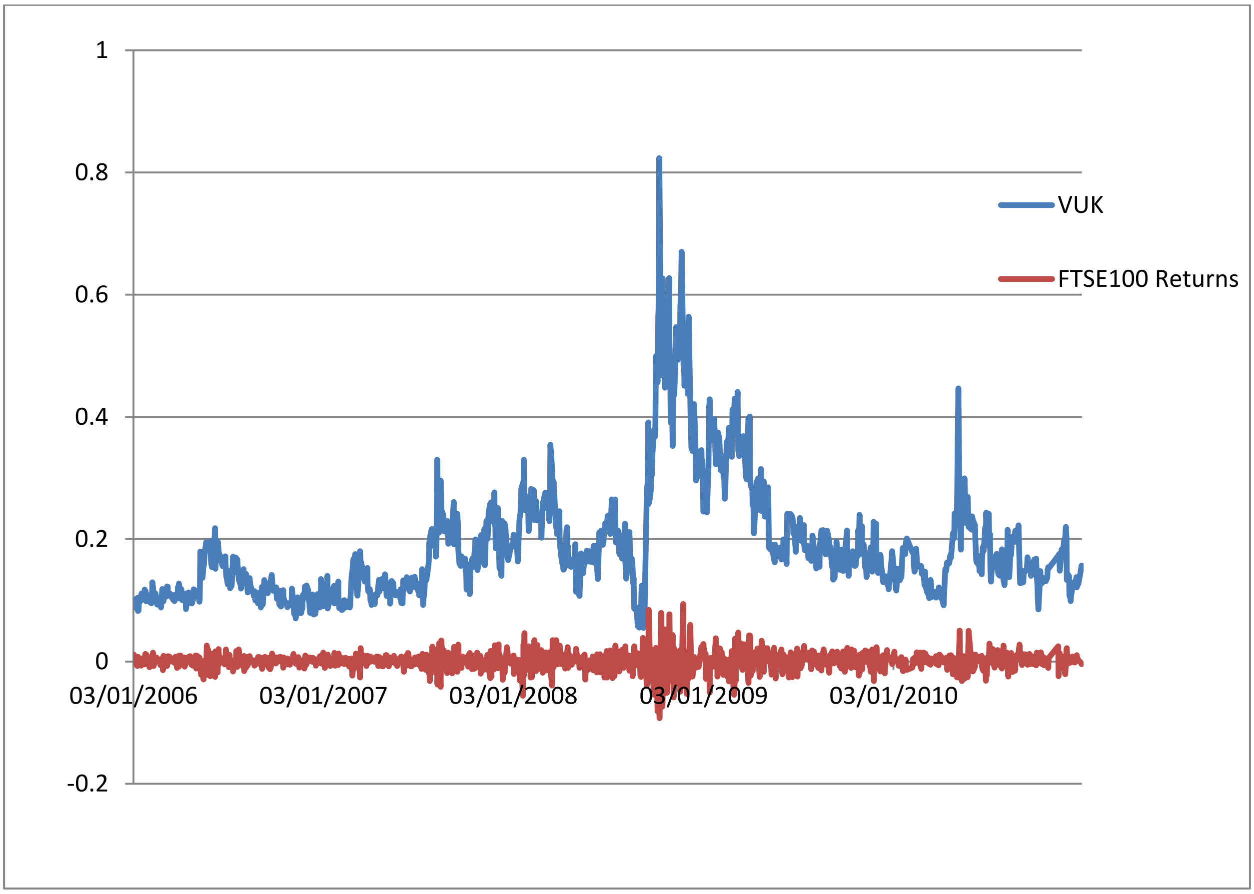
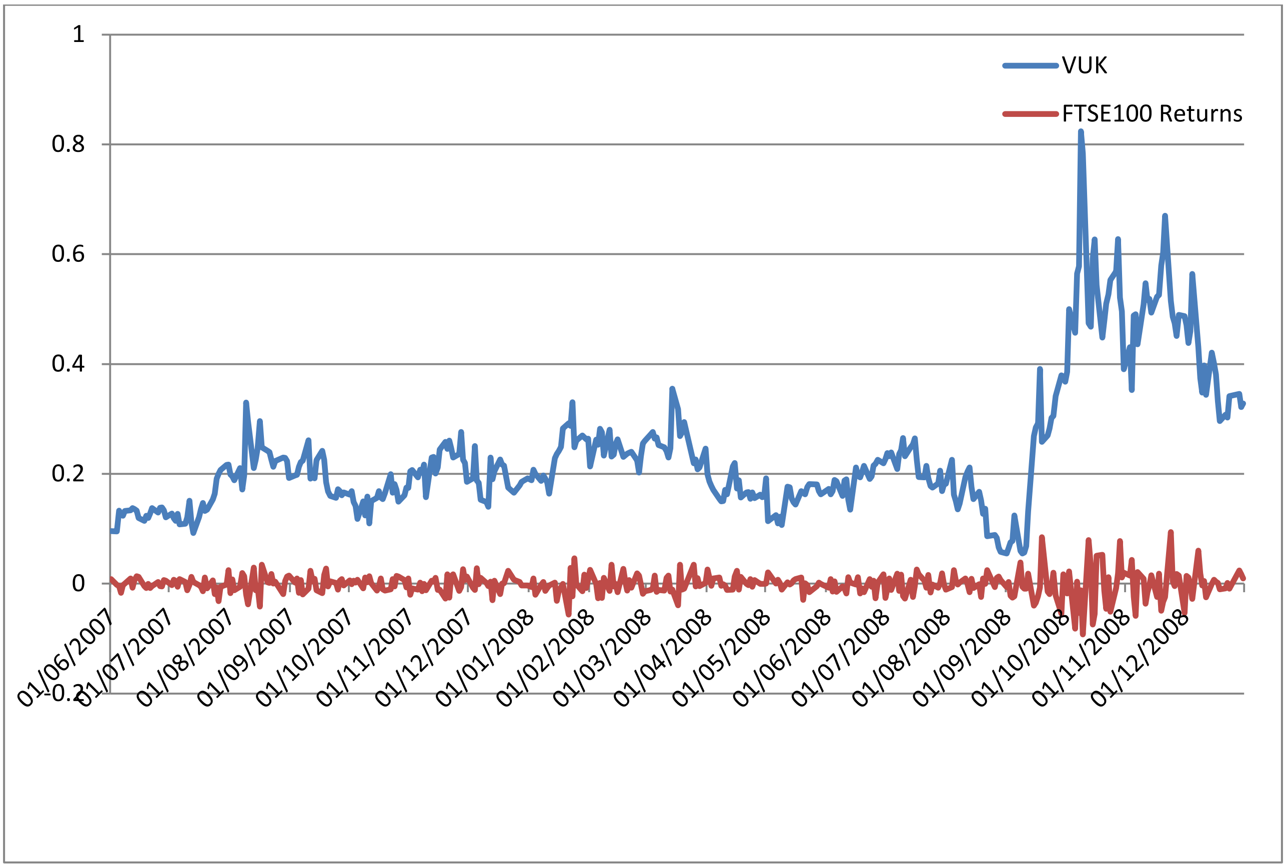


Figure 4.4 illustrates the time series relationship between the VUK and FTSE100 returns. Periods of high variance in the VUK, given by the blue line, correspond to periods of high volatility in FTSE100 daily returns. A shorter time period is presented

below in Figure 4.5. This allows a more clear view of the relationship between the VUK and FTSE100 returns during the financial crisis.

Figure 4.5 FTSE100 Daily Returns and the VUK: June 2007 through December 2008



The preceding figures provide visual evidence of a relationship between the two series which adds to the motivation for a more in-depth examination. The methodology described in section 4.4.3 will now be repeated with the VUK replacing the VIX throughout the analysis. However, due to a small number of observations missing from the Euronext LIFFE dataset the sample period begins in January 2006. Hence all computations are performed for a second time with 1232 observations.

4.5.4 Results

Results from the regression presented in equation (4.2) are presented in table 4.16.

Table 4.16 Model of daily changes in the VUK

$$\Delta VUK_t = \propto + \beta_1 VUK_{t-1} + \beta_2 D_1 RFTSE_t^+ + \beta_3 D_2 RFTSE_t^- + \beta_4 D_3 DEVMA_t^+ + \beta_5 D_4 DEVMA_t^- + \varepsilon_t$$

Variable	Whole Period	Pre-Crisis	Crisis	Post-Crisis
α	0.00739*** (0.0000)	0.024097*** (0.0075)	0.008763** (0.0164)	0.014507*** (0.0000)
β_1	0.002620 (0.8626)	-0.165814** (0.0239)	0.011600 (0.6321)	-0.027913 (0.1169)
β_2	-1.787660*** (0.0000)	-2.001821*** (0.0000)	-2.168635*** (0.0000)	-1.266847*** (0.0000)
β_3	0.137884 (0.5057)	-0.326692 (0.1054)	0.229380 (0.5085)	0.329834* (0.0648)
β_4	0.322267 (0.2054)	0.030054 (0.9690)	0.488113 (0.2120)	-0.242473 (0.4850)
β_5	-0.574559 (0.1320)	-1.008977** (0.0336)	-1.132080** (0.0426)	0.274088 (0.5961)
R^2	0.282543	0.473045	0.409652	0.150857

Figures in parentheses are p-values. *** significant at the 1% level; ** significant at the 5% level, * significant at the 10% level.

The results presented in Table 4.16 provide useful insights. Positive changes in the FTSE100 are strongly linked to negative changes in the VUK. This indicates that when stock returns are high the VUK volatility index falls. Except for the post-crisis period, the coefficients attached to negative changes in the FTSE100 are not statistically significant. These results suggest that the VUK responds asymmetrically to positive and negative contemporaneous returns. This is in sharp contrast to the findings of Simon (2003) on the VXN. Interestingly, during the crisis and pre-crisis periods the results are reversed. Positive deviations of the FTSE100 from its 5-day moving average are insignificant whereas negative deviations from its 5-day moving average are negative and significant. One interpretation of this result is that, when a negative trend is perceived during a predominantly falling market, demand for options for hedging and speculative purposes increases which in turn increases implied volatility. This is again in contrast to the findings of Simon (2003) who also finds that stronger positive trends lead to volatility index increases. However, Simon's work focuses on a bubble period where the upward trend allows buyers of calls to benefit from changes in the value of delta. It appears that option traders became increasingly sensitive to perceived departures of FTSE100 returns from mean reversion to a trending regime in the pre-crisis and crisis periods. Interestingly there is a marked decrease in explanatory power in the post-crisis period which implies a partial breakdown in the relationship following a period of significant market turbulence.

Table 4.17 FTSE100 Returns and the VUK Levels and First-Differences

Levels	$RFTSE_t = \propto + \beta_1 R + \beta_2 VUK_t + \varepsilon_t$			
Variable	**Whole Period**	**Pre-Crisis**	**Crisis**	**Post-Crisis**
α	0.004914*** (0.0004)	0.013044*** (0.0026)	0.005715** (0.0457)	0.007541*** (0.0003)
β_1	-0.105572*** (0.0063)	-0.042051 (0.6845)	-0.122845** (0.0413)	-0.074340 (0.1010)
β_2	-0.025780*** (0.0021)	-0.105587*** (0.0075)	-0.028171** (0.0402)	-0.034483*** (0.0035)
R^2	0.035180	0.100143	0.038314	0.038263
First-Differences	$RFTSE_t = \propto + \beta_1 RFTSE_{t-1} + \beta_2 \Delta VUK_t + \varepsilon_t$			
Variable	**Whole Period**	**Pre-Crisis**	**Crisis**	**Post-Crisis**
A	-0.000292 (0.4474)	0.000478 (0.3334)	-0.000937 (0.1787)	0.000621 (0.2804)
β_1	-0.066171 (0.2012)	0.098540 (0.2790)	-0.068439 (0.2444)	-0.026794 (0.6057)
β_2	-0.255348*** (0.0000)	-0.270458*** (0.0000)	-0.256089*** (0.0000)	-0.106361*** (0.0061)
R^2	0.264347	0.332181	0.268990	0.049677

*** significant at the 1% level; ** significant at the 5% level, * significant at the 10% level. Figures in parentheses are p-values.

The results presented in Table 4.17 illustrate that the signs on the coefficients are as expected. FTSE100 returns are found to be significantly and negatively related to contemporaneous values of the VUK in the levels and in first-differences. The effect is much more powerful in first-differences indicating that it is the increase in implied volatility rather than the level which is most strongly associated with negative returns on the FTSE100 index. It is clear that the first-differenced series of the VUK is a powerful tool for illustrating investor sentiment in the UK market and may be regarded as an appropriate fear gauge. The VUK in the levels is less important and may be misleading given that the VUK is non-stationary.[23] Other than during the crisis period the coefficient attached to the lagged FTSE100 returns is not significant.

Table 4.18 contains the regression results from running equations (4.9) and (4.12a) and is based on 47 observations over the period January 2007-December 2010.

Table 4.18 The Predictive Power of Volatility Forecasts (Levels)

$$\sigma_{t,T} = \alpha + \beta\sigma_t^{VIX,G,EWMA} + \varepsilon_{t,T}$$

$$\sigma_{t,T} = \alpha + \beta\sigma_t^{VIX} + \gamma\sigma_t^{G,EWMA} + \epsilon_{t,T}$$

Constant	VUK	GARCH	EWMA	R^2	D-W	Wald Test
-0.004903*** [0.001373]	0.789057*** [0.168193]			0.353361	1.53	122.4324 (0.0000)
-0.003350*** [0.001034]		0.690128***! [0.132273]		0.451548	2.18	142.1537 (0.0000)
-0.00264*** [0.000909]			0.564585***! [0.107235]	0.312943	1.83	1657442 (0.0000)
-0.004023*** [0.000815]	0.137502 [0.204264]	0.600873**! [0.255426]		0.454726	2.12	
-0.004750*** [0.001271]	0.631866***! [0.191217]		0.133058 [0.127044]	0.356719	1.60	

The Newey-West correction for autocorrelation and heteroskedasticity is used in the estimation. Figures in parentheses are standard errors. * Significantly different from zero at the 10% level; ** at the 5% level. *** at the 1% level. The Wald test is for the joint hypothesis that the intercept is equal to zero and that the coefficient attached to the volatility estimate is equal to one. The Wald F-statistic is reported and probability values for the test are in parentheses. ! Significantly different from one.

The results presented in Table 4.18 indicate that the intercept coefficients in each case are significantly less than zero. Furthermore, in the GARCH and EWMA estimations the slope coefficients are significantly less than one. This indicates that

[23] An Augmented Dickey Fuller test on the VUK with 3 lags gives a t-statistic of -3.438 and probability of (0.000). The VUK is found to be stationary in first differences.

the volatility forecasts are biased estimates of actual volatility. The results indicate that the VUK, GARCH and EWMA volatility forecasts all have significant forecasting power. The combination of a slope coefficient which is significantly greater than zero but significantly less than one and an intercept which is significantly less than zero indicates that when volatility forecasts are high relative to recent volatility their predictions of future volatility are too high. The VUK and EWMA forecasts each explain approximately 35% and 31% respectively of the overall variation in the level of realised volatility whilst the GARCH forecast explains approximately 45%. The model estimated including the GARCH and VUK forecasts produces a statistically significant GARCH coefficient and an insignificant coefficient for the VUK. This suggests that the GARCH encompasses the forecasting information provided by the VUK. When the EWMA and VUK forecasts are included the slope coefficient attached to EWMA becomes insignificant. Hence it is possible to conclude that the information provided by the EWMA volatility forecasts is contained in the VUK.

Table 4.19: The Predictive Power of Volatility Forecasts (First Differences)

$$\sigma_{t,T} - \sigma_{t-1,T-1} = \alpha + \beta\left[\sigma_t^{VIX,G,EWMA} - \sigma_{t-1,T-1}\right] + \varepsilon_{t,T}$$

$$\sigma_{t,T} - \sigma_{t-1,T-1} = \alpha + \beta\left[\sigma_t^{VIX} - \sigma_{t-1,T-1}\right] + \gamma\left[\sigma_t^{G,\ EWMA} - \sigma_{t-1,T-1}\right] + \varepsilon_{t,T}$$

Constant	VUK	GARCH	EWMA	R^2	D-W	Wald Test
-0.006780*** [0.000789]	0.871508*** [0.120965]			0.290096	1.73	47.92149 (0.0000)
-0.007138*** [0.419333]		0.963575** [0.419333]		0.318192	2.5	64.30148 (0.0000)
-0.007002 [0.005204]			0.773290 [0.613113]			
-0.008794*** [0.002064]	0.514960***! [0.137123]	0.647584 [0.439305]		0.385258	2.05	
-0.004706** [0.002394]	1.000037*** [0.204356]		-0.336619 [0.452916]	0.298675	1.78	

The White correction for heteroskedasticity is used in the estimation and figures in parentheses are standard errors. * Significantly different from zero at the 10% level; ** at the 5% level. *** at the 1% level. The Wald test is for the joint hypothesis that the intercept is equal to zero and that the coefficient attached to the volatility estimate is equal to one. The Wald F-statistic is reported and probability values for the test are in parentheses. ! Significantly different from one.

The results in Table 4.19 show that the VUK and GARCH forecasts by themselves have significantly positive coefficients which are not significantly different from one, however the intercepts are significantly negative. Hence the VUK and GARCH forecasts produce biased predictions of actual volatility changes. When these estimates are high relative to recent realised volatility they over-predict rising volatility. The GARCH forecast explains approximately 32% of the overall variation in realised volatility changes and the VUK approximately 29%. However the coefficient attached to the EWMA forecast is not significantly different to zero.

When both the GARCH and VUK forecasts are included in the model the VUK continues to enter with a significantly positive coefficient whilst the GARCH becomes insignificant. This is a reversal of the result found in the levels and suggests that in first-differences the VUK encompasses the forecasting information provided by the GARCH. When the EWMA and VUK are included the VUK volatility forecast remains significant and explains approximately 30% of the overall variation in realised volatility changes.

Overall these results suggest that the VUK and the GARCH model are powerful predictors of realised volatility in the FTSE100 index. They provide significant predictive power both in levels and first differences although the results also indicate that the forecasts of realised volatility are biased. Furthermore, the forecasting power of the EWMA is found to be insignificant in levels and in first-differences.

The VUK and FTSE100 Return Predictability

Potential stock market return predictability provided by the VUK is examined using equations (4.13a) and (4.13b) for a variety of lag lengths. Results are presented in table 4.20.

Table 4.20 Predictive Power of the Lagged VUK for FTSE100 Returns: 2006-2010

$$\boldsymbol{RFTSE_t = a + b_1 RFTSE_{t-1} + \ b_2 VIX_{t-n} + \ e_t}$$

$$\boldsymbol{RFTSE_t = a + b_1 RFTSE_{t-1} + \ b_2 \Delta VIX_{t-n} + \ e_t}$$

Constant	RFTSE(-1)	VUK(-1)	DVUK(-1)	VUK(-22)	DVUK(-22)	R^2
0.001248 (0.4192)	-0.089339*** (0.0152)	-0.006371 (0.4919)				0.008574
0.0000557 (0.8851)	-0.199698*** (0.0001)		-0.138912*** (0.0006)			0.070539
-0.000656 (0.4819)	-0.083473*** (0.0037)			0.003612 (0.4076)		0.007403
0.0000313 (0.9420)	-0.083445*** (0.0037)				0.009753 (0.4974)	0.007221

*Significant at the 10% level, ** at the 5% level, *** at the 1% level. Figures in parentheses are p-values.

Lagged values of the VUK were found to have no significant explanatory power for FTSE100 returns regardless of the lag length selected for the full period between 2006 and 2010. However some weak explanatory power was found in the change in the VUK lagged by one day. This suggests that options markets may be performing a weak price discovery function. The results presented in Table 4.21 illustrate that findings were broadly similar when the sample was restricted to the pre-crisis period from the beginning of January to the end of June 2007.

Table 4.21 Predictive Power of the Lagged VUK for FTSE100 Returns: Pre-Crisis Period January-June 2007

$$\boldsymbol{RFTSE_t = a + b_1 RFTSE_{t-1} + b_2 VIX_{t-n} + e_t}$$

$$\boldsymbol{RFTSE_t = a + b_1 RFTSE_{t-1} + b_2 \Delta VIX_{t-n} + e_t}$$

Constant	RFTSE(-1)	VUK(-1)	DVUK(-1)	VUK(-22)	DVUK(-22)	R^2
-0.011948*** (0.0000)	0.110197 (0.1401)	0.119037*** (0.0000)				0.117704
0.000442 (0.3519)	0.218390** (0.0404)		0.1085882** (0.0421)			0.056033
0.001375 (0.6099)	0.084239 (0.2805)			-0.007539 (0.7348)		0.007498
0.000516 (0.3225)	0.083141 (0.2933)				-0.002044 (0.9559)	0.006668

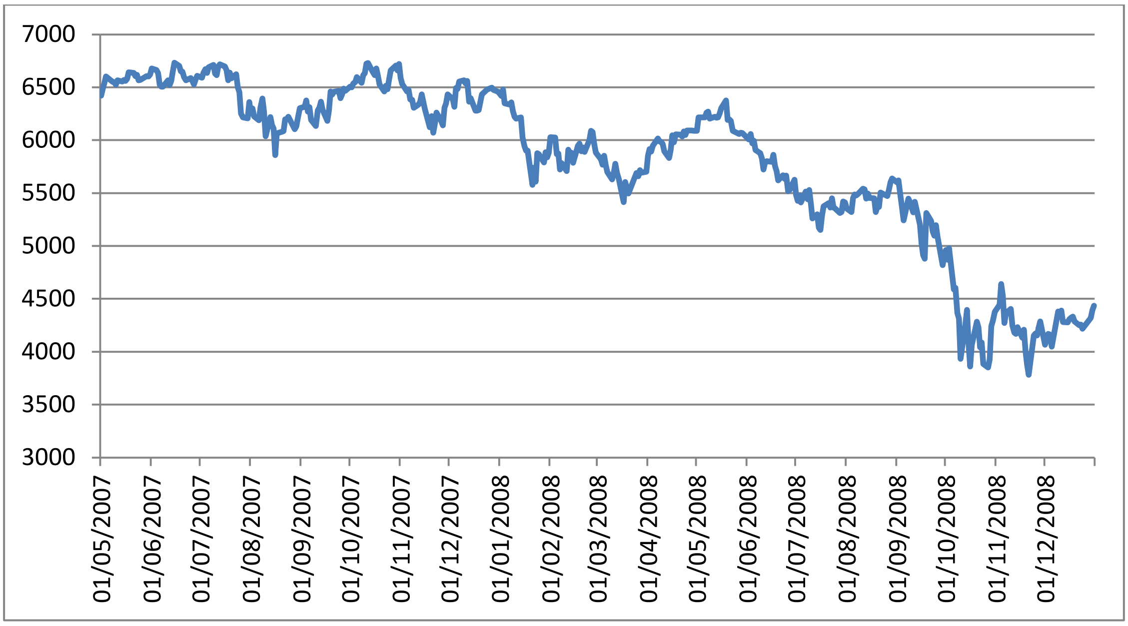
*Significant at the 10% level, ** at the 5% level, *** at the 1% level. Figures in parentheses are p-values.

The results are very similar to those found when the entire period is analysed. Again there is evidence of price discovery in the lagged change in the VUK. However during this period there is also some predictive power evident in the lagged VUK index level.

The most plausible explanation of the relatively weak results presented above is that a VUK volatility index has little value as an indicator of return predictability in the underlying equity market and only limited value as a price discovery mechanism. This explanation implies that professional options traders do not price future market moves into contracts with any degree of accuracy. Hence implied volatility does not provide a strong signal of crash expectations even during turbulent periods. However, despite the financial crisis first breaking in 2007 no significant negative returns were observed on the FTSE100 until mid-2008. It appears that the UK large capitalisation equity market remained remarkably robust to these events for a sustained time period. This is one possible contributory factor to the absence of a significant relationship between the lagged UK volatility index and FTSE100 returns.

Figure 4.6 presents the time series of FTSE100 prices for the period from 1st May 2007 to 31st December 2008.

Figure 4.6 FTSE100 Stock Index May 2007 – December 2008



It is clear from Figure 4.6 that the major decline in the FTSE100 index occurred in the second half of 2008. Hence for completeness a final crisis period will be selected from June 2nd 2008 when the FTSE100 closed at 6007 points to March 31st 2009 when it closed at 3926 points. Results from regressing the returns on the FTSE100 on the VUK in levels and first differences are presented in Table 4.22. The results presented use lag lengths of 1, 7 and 22 days.

Table 4.22 Predictive Power of the Lagged VUK for FTSE100 Returns: June 2008 – March 2009

$$RFTSE_t = a + b_1 RFTSE_{t-1} + b_2 VIX_{t-n} + e_t$$

$$RFTSE_t = a + b_1 RFTSE_{t-1} + b_2 \Delta VIX_{t-n} + e_t$$

Levels					
Constant	RFTSE(-1)	VUK(-1)	VUK(-7)	VUK(-22)	R^2
-0.003580 (0.4470)	-0.064908 (0.3899)	0.003533 (0.8556)			0.003533
-0.003768 (0.2857)	-0.069254 (0.2817)		0.004233 (0.7375)		0.005290
-0.006888 (0.1312)	-0.077542 (0.2522)			0.016422 (0.3124)	0.012804
First-Differences					
-0.0027176 (0.2181)	-0.291514*** (0.0143)	-0.205655*** (0.0084)			
-0.002483 (0.2838)	-0.069299 (0.2994)		0.007759 (0.9042)		0.004874
-0.002571 (0.2596)	-0.073004 (0.2683)			0.037297 (0.2601)	0.009339

*Significant at the 10% level, ** at the 5% level, *** at the 1% level. Figures in parentheses are p-values.

The results presented in Table 4.22 almost unanimously reject the notion of any return predictability contained in the implied volatility of FTSE100 options. Only the first-difference of the VUK with a single lag is found to contain any explanatory power, again consistent with a limited role in price discovery. Table 4.23 below contains contemporaneous values for the FTSE100 and VUK in the levels and first-differences for the same sub-period.

Table 4.23 The VUK and Contemporaneous FTSE 100 Returns

Constant	RFTSE(-1)	VUK	DVUK	R^2
0.006289 (0.1685)	-0.090875 (0.2730)	-0.027483 (0.1061)		0.030853
-0.001867 (0.2713)	-0.044181 (0.6001)		-0.264749*** (0.0001)	0.289492

*Significant at the 10% level, ** at the 5% level, *** at the 1% level. Figures in parentheses are p-values.

Table 4.23 contains the expected negative coefficients indicating that, contemporaneously, stock market returns and implied volatility move in opposite directions. However statistical significance is only found when the first-difference of the VUK is the explanatory variable. This is to be expected as the VUK, in common with the VIX, is non-stationary. The information in Table 4.23 provides support for the hypothesis that the VUK in first-differences performs a price discovery role for the underlying FTSE 100 index.

4.5.5 Conclusion

The results in this section are made possible by the construction of a unique volatility index that is used to draw meaningful inferences about the relationships between volatility implied by FTSE 100 index option prices and the underlying equity index.

The relationships identified between contemporaneous FTSE100 stock index returns and volatility indexes provide support for the conclusion of Whaley (2000) who finds that they are representative of the sentiment of market participants. Volatility indexes are found to provide a useful indication of future realised volatility. In general they provide better predictions than an EWMA model and at least as good predictions as an asymmetric GARCH model.

The results presented do not support the hypothesis that implied volatility indexes provide an accurate prediction of future market returns. Hence there is no evidence produced here that indicates an opportunity to earn consistent abnormal profits. There is some evidence of a role of options in price discovery which motivates further investigation in terms of trading volume and open interest. However there is no evidence in this chapter of market inefficiency. In other words it cannot be inferred that information about volatility is not being rapidly incorporated into prices. Furthermore, results are found to be fairly consistent across each sub-period of the financial crisis.

It is recognised that there are some limitations to the results which are governed by the availability of UK options market data. The use of daily data poses a problem of non-synchronisation given that the equity market and options market have different closing times. Nevertheless, if the impact of non-synchronous prices is random then the tests should be unbiased.

Chapter 5

An Analysis of Trading Volume and Open Interest in UK FTSE100 Index and Individual Equity Options Markets during the 2007-2008 Financial Crisis

5.1 Introduction and Motivation

The motivation for this chapter is to build on the analysis presented in Chapter 4 by undertaking an investigation of investor trading behaviour in FTSE100 index and single equity options traded on LIFFE. More precisely, the relationship between the aggregate large capitalisation market, financial stocks and options underlying the index and the financial stocks will be examined in order to contribute to the debate on the means by which information is incorporated into asset prices. The central objective of this chapter is to establish whether any predictive power for financial stock returns can be identified in options market trading behaviour and, if so, how strong this relationship is.

Options are not necessarily redundant assets, even though their returns can be replicated by employing a dynamic trading strategy which involves a combination of stocks and riskless assets. The reason for this is that they can provide investors with a low cost, leveraged alternative to taking an equity position and, furthermore, do not suffer from the short-sales restrictions that are present in equity markets. So, in incomplete markets where price is driven by trading, informed traders who take advantage of this alternative will contribute to price discovery in equity markets. Although the majority of studies do not find evidence of predictability at an aggregate level during periods of relative tranquillity, it is nevertheless worthwhile to test for any predictability (particularly using individual securities related to the financial sector) during a period of significant financial turbulence. If significant predictive power can be identified than this will pose a challenge for the efficient markets hypothesis, albeit due to limited arbitrage.

It is intuitive to expect that an increase in call trading volume will be observed in rising markets, as traders seek to benefit from greater leverage. Similarly when the market is declining, more put trading volume is likely to occur as a result of speculative or hedging demand aimed at overcoming short sales restrictions or achieving portfolio insurance. It follows that pessimistic investor expectations should result in an increase of trading in puts relative to that in calls. Again it is likely that relatively fewer call positions will be opened for speculative purposes when investors do not expect prices to rise with the consequent impact on relative trading volume. Even though it is possible to profit from the time decay by writing call options the purchase of puts provides a much more attractive opportunity. Furthermore, as suggested by Simon (2003) the absolute impact on call trading volume is likely to be tempered somewhat by the actions of risk-averse investors who view call options as a low risk means of investing in stocks. Should investor expectations be particularly pessimistic towards companies in the financial sector then the imbalance in trading should be most pronounced in options written on the stocks of financial firms.

Net open interest provides an additional source of information on option trading behaviour. Open interest indicates the number of option contracts which remain outstanding at the close of each trading day. As option traders themselves write options, open interest may be regarded as endogenous and therefore reflect the beliefs and risk preferences of options traders. Beliefs and risk-preferences are both factors that are prominent in the field of behavioural finance. Trading volume comprises four components; opening a contract to buy, opening a contract to sell, closing out a contract to buy and closing out a contract to sell. The last two components reduce open interest, so on any given day an increase in trading volume could have a net effect of either increasing or decreasing open interest. A positive change in open interest indicates that more contracts are being opened than are being closed out thus it provides a useful indicator of option trading behaviour. However, open interest also has its limitations as it only measures the number of contracts outstanding.

The contemporaneous relationship between relative trading volume/open interest and index/equity portfolio returns will be also be examined for evidence of price discovery. Furthermore, a behavioural approach will be formulated to isolate trading behaviour in response to a series of return innovations of the same sign.

Daily trading volume and open interest of FTSE100 and single equity put and call options traded in the UK options market are recorded by Euronext LIFFE. The index options are European-style whilst the equity options are American-style. All of the options in each category trade with a variety of strike prices and mature on the third Friday of the delivery month. Time series of trading volume and open interest ratios for index and single stock options will be analysed for the period 2006-2010 in an attempt to detect any changes in behaviour to occur during this period and to identify any predictive power that may be inferred from the data.

This chapter will examine and seek to address the following questions which are related to those posed in Chapter 4:

- Is there any significant predictive relationship between the relative trading volume and open interest of put and call options written on the FTSE100 and future spot market returns?
- Is there any significant predictive relationship between the relative trading volume and open interest of put and call options written on financial stocks and future spot market returns?

- Is it possible to infer any change in investor behaviour across each stage of the financial crisis?
- Is relative trading behaviour influenced by a series of return innovations of the same sign?

5.2 Literature

There is seemingly little literature available that relates trading volume to crash expectations although a number of studies have focused on the informational content of trading volume and open interest during periods of relative tranquillity in markets and during periods of relative turbulence.

Manaster and Rendleman (1982) produced one of the first investigations into market expectations embedded into option prices. The purpose of this study was to determine whether the options market responds more quickly than the stock market to the arrival of new information. Manaster and Rendleman used daily data to compute the stock price implied by the Black-Scholes model and compared this with the market price. Their results indicated that the implied prices contain information about future stock returns. However they are unable to establish whether traders could use this information to earn excess returns.

Stephan and Whaley (1990) use intraday data on CBOE options from the first quarter of 1986 to produce implied stock prices. They argue that intraday data produces more reliable results as it overcomes the problem of non-contemporaneous closing prices. The change in implied stock price is compared to the change in the actual stock price to identify a lead-lag relationship. Stephan and Whaley conclude that stock returns lead option returns by an average of about fifteen to twenty minutes.

One important concern regarding tests of implied stock prices is that they are likely to be sensitive to the method of volatility computation.

Figlewski and Webb (1993) investigate the role of CBOE options in improving transactional and informational efficiency in the S&P500 stock market in the context of short-selling restrictions. The relationship between short interest and stocks with and without exchange-traded options is examined.[24] Short interest should be higher for stocks with options written on them because the puts can be used as an alternative to short-selling by constrained investors. Market makers subsequently take short positions to cover the options written, leading to higher short interest for stocks with corresponding exchange-traded options. Figlewski and Webb hypothesise that there should be positive correlation between short interest and the difference between put and call implied volatilities. They conclude that the relationships between short interest and exchange-traded options and between short interest and implied volatilities indicates that option trading contributes to transactional and informational efficiency in stock markets.

Mayhew, Sarin and Shastri (1995) analyse market microstructure and note that option margin requirements play a role in efficiency because higher margins reduce liquidity. This in turn decreases the rate of information flow to equity markets because of the impact on arbitrage links, relative trading costs and investor migration. In particular less-informed investors, who are assumed to be more capital constrained, are likely to migrate in response to margin changes which in turn affects relative concentration. Mayhew, Sarin and Shastri find evidence that supports migration between markets and changes in relative concentration. They also note

[24] Short interest is defined as the number of shares that have been sold short but not yet covered by repurchasing.

that the 1986 decrease in margin on options traded on the CBOE increased information to the stock market, but that the margin increase of 1998 resulted in no change in the underlying market. The study has a behavioural aspect as it is uninformed traders that are most sensitive to margin changes and are therefore key to the results.

Amin and Lee (1997) examine the relationship between option trading volume and firm-specific news and produce evidence of price discovery. Their sample contains options traded on the CBOE in 1988 and 1989 with corresponding stock prices from the New York and American stock exchanges. Amin and Lee present evidence of an increase in option market activity up to four days prior to an earnings announcement which is sustained for several days afterwards. Of course, the additional volume could be a response to volatility risk or an opportunity for volatility speculation where traders construct strategies such as straddles, strangles, strips and straps. However, Amin and Lee find that the trading volume is directional as put option open interest increased prior to negative earnings news and decreased prior to positive earnings news. This finding implies that predictability may be found in open interest data which in turn will be a reasonable proxy for private information. Furthermore, Amin and Lee find that option traders also provide private information to the market during non-announcement periods.

Easley, O’hara and Srinivas (1998) also investigate the role of options in informational efficiency where traders have heterogeneous information sets. They find evidence to indicate a link between trading volume and stock returns, which is independent of significant events in the market such as takeover announcements. Stock price changes are found to lead options market trading volume but when option trades are categorised as driven by good news or bad news they find that trading volume provides information about future stock price changes.

Chakraverty, Gulen and Mayhew (2004) investigate the role of options in price discovery using individual equity options traded on the CBOE between 1988 and 1992. They find that options do perform a price discovery function with the information flow greatest when trading volume is high. The evidence of price discovery does not imply that informed traders use their information to trade in options markets although Chakraverty *at al* do not rule out the possibility of this information being made public through the hedging decisions of informed market makers. If spot market traders observe these ‘signals’ then this would be akin to trading on the basis of ‘inside’ information which, if profitable, represents a violation of the strong form of the efficient markets hypothesis.

Cao, Chen and Griffin (2005) investigate the informational content of trading volume in CBOE options between 1986 and 1994 prior to merger and acquisition activity. They find that the highest pre-announcement buyer-initiated call trading volume is associated with the highest announcement day returns. This is interpreted as informed options traders playing a key role in price discovery for extreme informational events. Cao *et al* did find that trading volume of call options written on firms prior to a takeover announcement had predictive power for the magnitude of takeover premiums. Cao *et al* find little to suggest that option trading volume predicts stock returns during periods when market behaviour is normal. This finding is supported by Chan, Chung and Fong (2002) who find that option trading volume provides no predictive power.

Pan and Poteshman (2006) investigate the information regarding future stock price movements contained in the trading volume of CBOE options. The authors' data set allows them to separate public information from that which is privately held and to categorise option traders by degree of sophistication. They find that the trading behaviour of informed traders demonstrates significant predictability for future stock returns. The information provided by option trading volume is found to take several weeks to be impounded into stock prices. However it is argued that this finding does not contradict the efficient markets hypothesis simply because the information used in the tests would not have been publicly available at the time. One interesting point is that although informed trading is evident in the individual stock option market there was no such evidence to be found in the index option market. This indicates that informed investors do not have access to private information at an aggregate level.

Buraschi and Jiltsov (2006) examine S&P500 index option data under the assumption that option market participants have heterogeneous beliefs. This is used to establish an option pricing model under conditions of uncertainty. Importantly for this study Buraschi and Jiltsov establish a link between these heterogeneous beliefs and option market open interest. They demonstrate that a one standard deviation increase in an index of heterogeneous beliefs results in a 20% increase in option open interest. This study differs from previous work in that index options, where trades are much less likely to be driven by private information, are considered.

Cao and Yang (2009) develop a theoretical model which considers traders with heterogeneous beliefs and is extended to multiple periods. They find that public information that is likely to result in investor disagreement has different implications for participants in equity and options markets. Cao and Yang assert that trading volume in equities increases in response to public news and diffuses slowly, whereas option trading is clustered before and during the public news event. A limitation of Cao and Yang's approach is that it excludes the possibility of investor acquisition of private information.

Chang, Hsieh and Lai (2009) examine the Taiwan stock market for any evidence of stock return predictability in option trading volume. In particular they investigate the impact that option market activity of foreign investors has on domestic returns. It is hypothesised that the high liquidity and low transactions costs in the options market attract informed investors more than the related equity markets. It follows that activity in the options market is likely to provide information on the future movement of the underlying asset. Chang *et al* are unable to find any predictability for stock market returns using aggregate trading volume or open interest lagged up to seven days. However, when the data was disaggregated, strong predictive power was found in the trading volume of foreign institutional investors.

5.3 Data

Daily trading volume and open interest of European-style FTSE100 index and American-style individual equity put and call options are collected from Euronext LIFFE. Stock prices of the financial companies underlying the individual equity options are collected from Datastream. The financial stock portfolio consists of fifteen stocks from the banking, financial services and insurance sectors. The stocks selected correspond to those financial companies with associated options traded on LIFFE. The list of companies with their LIFFE codes and sectors is presented in Appendix 3. The sum of all put and call options traded on a given day are used to construct the first series of trading volume and open interest ratios for the empirical tests. However, following Pan and Poteshman (2006) out-of-the-money options are also used for the empirical work in order to capture leverage effects. The rationale is that, if an investor has private positive or negative information, greater leverage can be achieved by purchasing out-of-the-money calls or puts respectively. Furthermore, out-of-the-money options typically have higher trading volume than those in-the-money. The combined effect is that any predictability of future returns is likely to be most evident in results produced from analysis of out-of-the-money options.

Data on the FTSE100, to be employed in the analysis that follows, is the same set as that used in the previous chapter. Additional stock price data on the financial firms consists of end of day prices and is collected from Datastream. The entire sample period is once more from January 2006 to December 2010.

An initial inspection of the data is performed using correlation across a variety of variables. Summary statistics for trading volume and open interest ratios are presented in Table 5.1. These are split by series generated using all options and those generated using out-of-the-money options only. Correlations between the FTSE100 index and trading volume/open interest for FTSE100 index puts and calls for the entire period and sub-periods are presented in Table 5.2. The pre-crisis, crisis and post-crisis sub-periods follow the original specification set out in Chapter 4.

Table 5.1 Summary Statistics for Trading Volume and Open Interest Ratios

Panel A: FTSE100 Index Options

Variable	Mean	Standard Deviation	Skewness	Kurtosis (raw)	ρ_1	ρ_2	ρ_3	ρ_4
All Options								
$PCRTV_t$	0.571976	0.119129	-0.192775	2.840329	0.212	0.170	0.143	0.120
$PCROI_t$	0.539782	0.069396	-2.001669	12.06661	0.044	0.641	0.221	0.425
Out-of-the-Money Options								
$PCRTV_t$	0.584723	0.130215	-0.209123	2.753567	0.208	0.197	0.172	0.173
$PCROI_t$	0.611242	0.142323	-0.921888	3.192259	0.980	0.966	0.953	0.943

Panel B: Equity Portfolio Options

Variable	Mean	Standard Deviation	Skewness	Kurtosis (raw)	ρ_1	ρ_2	ρ_3	ρ_4
All Options								
$PCRTV_t$	0.879808	0.098967	-0.422893	1.955826	0.912	0.882	0.877	0.866
$PCROI_t$	0.715245	0.201475	0.466646	1.283746	0.994	0.989	0.984	0.979
Out-of-the-Money Options								
$PCRTV_t$	0.530766	0.195100	-0.093838	2.305914	0.169	0.116	0.039	0.072
$PCROI_t$	0.466050	0.135393	0.915698	4.046132	0.968	0.946	0.926	0.909

$PCRTV_t$ is the put call ratio for trading volume

$PCROI_t$ is the put call ratio for open interest

For all options the mean values of the put to call trading volume ratio and of the put to call open interest ratio lie between 0.466 and 0.89. This indicates that, on average throughout the entire period, there is more trading activity in FTSE100 index and individual equity puts than in the respective calls. The mean values increase when the sample is restricted to out-of-the-money index options but decrease when restricted to out-of-the-money equity options. This indicates that a greater amount of put relative to call trading is taking place in this moneyness range for index options but the reverse is true for equity options. All of the distributions for trading volume are platykurtic, whilst the distributions for the open interest ratio are leptokurtic apart from that for open interest for all equity options. The presence of strong autocorrelation and a high level of kurtosis indicates a significant departure from normality. To correct for this, the Newey-West procedure for autocorrelation and heteroskedasticity will be used in the empirical tests.

The correlation coefficients presented in the following tables provide an initial indication of the relationship between each ratio and the portfolios underlying the option contract.

Table 5.2 Correlation of FTSE100 Index and Index Returns with Index Option Trading Volume, January 2006-December 2010

Panel A: All Options

Entire Period				
	TTV	PCR_{TV}	TVP	TVC
FTSE100	-0.10633*** (-3.7330)	0.251954*** (9.0863)	-0.0023 (-0.0802)	-0.2028*** (-7.2280)
RFTSE100	-0.13388*** (-4.7150)	-0.18974*** (-6.7445)	-0.21052*** (-7.5157)	0.003548 (0.1238)
Pre-Crisis				
FTSE100	-0.21822** (-2.2913)	-0.02847 (-0.2918)	-0.23461** (-2.4731)	-0.11511 (-1.1874)
RFTSE100	-0.17666 (-1.8391)	-0.26243*** (-2.7868)	-0.2993*** (-3.2142)	0.06420 (0.6592)
Crisis				
FTSE100	-0.09782** (-1.9658)	0.14187*** (2.8665)	-0.03184 (-0.6370)	-0.10913
RFTSE100	-0.09025* (-1.8125)	-0.20844*** (-4.2624)	-0.22668*** (-4.6547)	-0.0334** (-2.1957)
Post-Crisis				
FTSE100	-0.22443*** (-4.945)	0.22113*** (4.8684)	-0.14887*** (-3.2324)	-0.33614*** (-7.6331)
RFTSE100	-0.0985** (-2.1252)	-0.2133*** (-4.6877)	-0.20997*** (-4.6111)	0.075338 (1.6222)

Panel B: Out-of-the-Money Options

Entire Period				
	TTV	PCR_{TV}	TVP	TVC
FTSE100	-0.1127*** (-3.9568)	0.224527*** (8.0379)	-0.00382 (-0.1333)	-0.19717*** (-7.0160)
RFTSE100	-0.09739*** (-3.4135)	0.029 (1.0121)	-0.06213** (-2.1715)	-0.10186*** (-3.5719)
Pre-Crisis				
FTSE100	-0.17312* (-1.8012)	0.0474375 (0.4866)	-0.14196 (-1.4695)	-0.14102 (-1.4597)
RFTSE100	-0.15845 (-1.6444)	-0.02422 (-0.2482)	-0.14619 (-1.0198)	-0.10595 (-1.0918)
Crisis				
FTSE100	0.00123 (0.0242)	0.16323*** (3.2966)	0.02481 (0.4945)	-0.11777** (-2.36301)
RFTSE100	0.01643 (0.3273)	0.06006 (1.1989)	-0.02535 (-0.5053)	-0.15407*** (-3.1070)
Post-Crisis				
FTSE100	-0.21917*** (-4.8230)	0.23667*** (5.2302)	-0.12793*** (-2.7695)	-0.34762*** (-7.9601)
RFTSE100	0.04425 (0.9509)	-0.04492 (-0.9655)	-0.13027*** (-2.8211)	-0.01076 (-0.2311)

Figures in parentheses are t-statistics. The relevant 1%, 5% and 10% critical values for the pre-crisis sub-period are 2.617, 1.98 and 1.658 respectively and 2.576, 1.96 and 1.645 respectively for the remaining sub-periods and entire period.

FTSE100 is the FTSE100 level

RFTSE100 is FTSE100 returns

TTV is total trading volume

PCR_{TV} is the put/call ratio for trading volume

TVP is total trading volume of puts

TVC is total trading volume of calls

First the correlation coefficients for all options, presented in Table 5.2, Panel A, are considered. Total trading volume, relative trading volume and put option trading volume are negatively correlated with index returns reflecting the increase in demand for either hedging or speculative purposes when the market declines. The negative relationship with put volume is strongest in each period which may be due to the value of put options in portfolio insurance strategies or to facilitate momentum strategies. Trading volume of call options is positively related to index returns in all periods other than the crisis period which may be interpreted as a reflection of the benefit of holding calls in market rallies. However the negative relationship, small but significant at the 5% level, during the crisis period indicates an increased demand for calls during a significant market decline. This observation accords with the finding of Simon (2003) that investors will purchase calls as a less risky alternative to stocks in strongly bearish markets.

Correlation coefficients for out-of-the-money options are presented in Table 5.2, Panel B. The results are broadly similar although there is less statistical significance in the pre-crisis and crisis periods.

Table 5.3 Correlation of FTSE100 Index with Index Option Open Interest, January 2006-December 2010

Panel A: All Options

Entire Period				
	TOI	PCR_{OI}	OIP	OIC
FTSE100	-0.36142***	0.355578	-0.085247	-0.516844
	(-13.4333)	(13.1844)***	(-2.9651)***	(-20.9226)***
RFTSE100	0.003158	0.001738	0.003149	0.00209
	(0.1094)	(0.0602)	(0.1091)	(0.0724)
Pre-Crisis				
FTSE100	0.389249***	0.354352***	0.436886***	0.308857***
	(4.3095)	(3.8645)	(4.9531)	(3.3120)
RFTSE100	0.006578	-0.00475	0.006198	0.006847
	(0.0671)	(-0.0484)	(0.0632)	(0.0698)
Crisis				
FTSE100	-0.46813***	0.860454***	-0.204434***	-0.646386***
	(-10.6084)	(33.8168)	(-4.1821)	(-16.9642)
RFTSE100	-0.02135	0.003215	-0.02248	-0.018612
	(-0.4276)	(0.0644)	(-0.4502)	(-0.3728)
Post-Crisis				
FTSE100	-0.16797***	-0.06782***	-0.150018***	-0.12044***
	(-3.5864)	(-1.4308)	(-3.1936)	(-2.5536)
RFTSE100	0.037415 (0.7880)	0.022996 (0.4841)	0.041116 (0.8661)	0.01692 (0.3562

Panel B: Out-of-the-Money Options

Entire Period				
	TOI	PCR_{OI}	OIP	OIC
FTSE100	-0.26633*** ((-9.5436)	0.13763*** (4.7992)	0.48130*** (18.9654)	-0.69801*** (-33.6679)
RFTSE100	0.05746** (1.9878)	0.13763*** (4.7992)	0.14411*** (5.0301)	-0.10569*** (-3.6712)
Pre-Crisis				
FTSE100	0.19101* (1.9556)	0.85521*** (16.5833)	0.74993*** (11.3931)	-0.62859*** (-8.1227)
RFTSE100	-0.00585 (-0.0589)	0.27933*** (2.9235)	0.17899* (1.8282)	-0.22685** (-2.3408)
Crisis				
FTSE100	-0.06596 (-1.31873)	0.91932*** (46.6054)	0.83299*** (30.0355)	-0.86726*** (-34.753)
RFTSE100	0.06045 (1.2082)	0.15664*** (3.1640)	0.15351*** (3.0993)	-0.10153** (-2.03606)
Post-Crisis				
FTSE100	-0.10788** (-2.2710)	0.87107*** (37.1162)	0.62269*** (16.6548)	-0.87285*** (-37.4333)
RFTSE100	0.09163* (1.9258)	0.11887** (2.5055)	0.13286*** (2.8053)	-0.10758** (-2.2647)

Figures in parentheses are t-statistics. The relevant 1%, 5% and 10% critical values for the pre-crisis sub-period are 2.617, 1.98 and 1.658 respectively and 2.576, 1.96 and 1.645 respectively for the remaining sub-periods and entire period.

Table 5.3 contains correlation coefficients between FTSE100 returns and open interest with each variable defined in the same way as in Table 5.2. In Panel A, where all options in the sample are included, little correlation is apparent with FTSE100 returns. However there is strong and significant correlation between each variable and the level of the FTSE100. The signs are somewhat unexpected showing negative correlation between the FTSE100 level and call open interest and positive correlation between the FTSE100 level and put open interest. Similar results are reported in Panel B with the put call ratio for open interest positively correlated with the FTSE100 level across all periods.

The correlation tests are repeated for the portfolios of single equity options and the results presented in Tables 5.4 and 5.5.

Table 5.4 Correlation of Equity Option Portfolio Returns with Equity Option Trading Volume, January 2006-December 2010

Panel A: All Options

	TTV	**PCR_{TV}**	**TVP**	**TVC**
Entire Period	-0.05664** (-1.9629)	-0.07147** (-2.4791)	-0.05703** (-1.9762)	0.058977** (2.0440)
Pre-Crisis	-0.09433 (-0.9522)	-0.12368 (-1.2527)	-0.09833 (-0.9930)	0.094445 (0.9534)
Crisis	-0.03261 (-0.6199)	-0.09043* (-1.7252)**	-0.03354 (-0.6376)	0.110162** (2.1059)
Post-Crisis	0.058231 (1.2686)	-0.1066** (-2.3317)	0.0578899 (1.2613)	0.099807** (2.1816)

Panel B: Out-of-the-Money Options

	TTV	**PCR_{TV}**	**TVP**	**TVC**
Entire Period	-0.03481 (-1.2051)	-0.099867*** (-3.4725)	-0.06448** (-2.2354)	0.012305 (0.4258)
Pre-Crisis	-0.0441 (-0.4437)	0.043213 (0.4347)	-0.03102 (-0.31185)	-0.038362 (-0.3858)
Crisis	-0.0616 (-1.1726)	-0.141454*** (-2.7149)	-0.08746* (-1.6682)	-0.01709 -0.3248
Post-Crisis	0.024492 (0.5328)	-0.088688* (-1.9365)	-0.01351 (-0.2939)	0.063912 (1.3928)

Figures in parentheses are t-statistics. The relevant 1%, 5% and 10% critical values for the pre-crisis sub-period are 2.617, 1.98 and 1.658 respectively and 2.576, 1.96 and 1.645 respectively for the remaining sub-periods and entire period.

Correlation is again weak although there is consistent negative correlation between returns on the equity portfolio and the put call ratio for all options and for out-of-the-money options. There is also positive correlation between returns on the equity portfolio and call trading volume when all options are examined but not for the sub-sample of out-of-the-money options. The signs attached to significant coefficients accord with expectations as negative returns are associated with increases in put relative to call trading volume and, for the entire period when all options are included, with increases in total trading volume.

Table 5.5 Correlation of Equity Option Portfolio with Equity Option Open Interest, January 2006-December 2010

	TOI	**PCR_{OI}**	**OIP**	**OIC**
Entire Period	-0.00201 (-0.0696)	-0.03946 (-1.3662)	-0.00522 (-0.1808)	0.027011 (0.9349)
Pre-Crisis	-0.0499 (-0.5021)	0.118696 (1.2014)	-0.04706 (-0.4735)	-0.10058 (-1.0160)
Crisis	-0.03433 (-0.6527)	0.107054** (2.0458)	-0.03386 (-0.6437)	-0.02383 (-0.4528)
Post-Crisis	0.050875 (1.1079)	0.051632 (1.1244)	0.051006 (1.1107)	0.03434 (0.7472)

Panel B: Out-of-the-Money Options

	TOI	**PCR_{OI}**	**OIP**	**OIC**
Entire Period	-0.03354 (-1.1610)	-0.12492*** (-4.356)	0.04362 (1.5104)	-0.10082*** (-3.5060)
Pre-Crisis	-0.02913 (-0.2929)	-0.25863*** (-2.6908)	0.04875 (0.4905)	-0.11482 (-1.1616)
Crisis	-0.03716 (-0.7065)	-0.09686* (-1.8490)	0.05226 (0.9943)	-0.13828*** (-2.6528)
Post-Crisis	0.010074 (0.2191)	-0.14898*** (-3.27673)	0.09939** (2.1724)	-0.12577*** (-2.7573)

Figures in parentheses are t-statistics. The relevant 1%, 5% and 10% critical values for the pre-crisis sub-period are 2.617, 1.98 and 1.658 respectively and 2.576, 1.96 and 1.645 respectively for the remaining sub-periods and entire period.

The coefficients presented in Table 5.5 are mostly insignificant when all options are included and indicate little correlation between the equity option portfolio and corresponding open interest with no consistency in sign. However, there is considerably more evidence of correlation when the sample is confined to out-of-the-money options. The put-call ratio for open interest is negatively related to returns on the underlying equity portfolio. Open interest on calls is also negatively related to returns on the equity portfolio.

The information contained in the preceding correlation statistics provides sufficient motivation for further and more robust tests of the relationship between option trading volume and stock market returns. Although the relationship between open interest and stock market returns is much weaker it may still be useful to proceed with similar tests, particularly using out-of-the-money options written on the stocks in the equity portfolio.

5.4 Methodology

The key explanatory variable is a statistic which represents lagged monthly put relative to call trading volume. Pan and Poteshman (2006) argue that the put call ratio presented in equation (5.1) provides a parsimonious representation of the information content of trading volume. In particular the put call ratio of out-of-the-money options are regarded as useful sources of information.

$$PCRTV_t = \frac{TVP_t}{TVP_t + TVC_t} \qquad (5.1)$$

Where:

TVP_t is the trading volume of FTSE 100 European-style index put options

TVC_t is the trading volume of FTSE 100 European-style index call options

$PCRTV_t$ is the Put-Call Ratio for trading volume of the index options

If trading volume on calls increases, because of perceived positive information this will reduce the value of the put-call ratio assuming that put trading volume does not increase by a corresponding or greater amount. The converse will be true if trading volume on puts increases because of perceived negative information.

Following the work of Amin and Lee (1997) and Buraschi and Jiltsov (2006) open interest will be analysed. As in Amin and Lee the following put-call ratio constructed from open interest will be examined.

$$PCROI_t = \frac{OIP_t}{OIP_t + OIC_t} \qquad (5.2)$$

Each put-call ratio will be lagged by 1 day and the regression will include the lagged index as a control variable. Consistent with the analysis in Chapter 4, the model is re-estimated using a variety of lag lengths with those of 7 and 22 days reported for completeness.

The regression given in equation (5.3) will be run to examine the predictive power of relative put/call trading volume for returns on the UK, large market capitalisation, aggregate stock market. The lagged FTSE100 return series is included as a control variable.

$$RFTSE_t = a + b_1 RFTSE_{t-1} \ \ b_2 PCR^{TV,OI}{}_{t-k} + \ e_t \qquad (5.3)$$

Where k is either 1, 7 or 22.

Trading Volume and Open Interest in the Financial Sector

Equation (5.3) will be re-run although this time the relative trading volume statistic will be constructed using the portfolio of options written on financial stocks.

$$PCRTV_E = \frac{TV_P}{TVp + TV_C} \tag{5.4}$$

Where:

TV_P is the aggregate trading volume of American-style put options written on UK banking stocks

TV_C is the aggregate trading volume of American-style call options written on UK banking stocks

$PCRTV_E$ is the put/call trading volume ratio for options written on the constituents of the equity portfolio

Finally the return on the financial stock portfolio will be regressed on the index option trading volume and open interest ratios respectively.

The relationship between returns on the portfolio of financial stocks and trading volume/ open interest ratios is also examined contemporaneously. No initial assumption regarding the direction of the relationship is made and the regressions given in equations (5.5) and (5.6) are run.

$$RPort_t = a + b_1 RPort_{t-1} + b_2 PCR_t^{TV,OI} + e_t \tag{5.5}$$

$$PCR_t^{TV,OI} = a + b_1 RPort_t + b_2 RPort_{t-1} + e_t \tag{5.6}$$

Where:

$PCR_t^{TV,OI}$ is the put-call ratio for trading volume or open interest.

$Rport_t$ is the return on the portfolio of financial stocks.

A significant value of β_2 in equation (5.5) would indicate that the relative trading volume/open interest of put and call options serves a price discovery function. This implies that the trading behaviour of professional options traders results in private information being impounded into equity prices via a lead-lag mechanism. Significant values of β_1 and β_2 in equation (5.6) would indicate that trading volume/open interest responds to contemporaneous and lagged values of the stock portfolio.

A behavioural approach is taken to examine the response of trading volume and open interest to a series of return innovations of the same sign. The regression given by equation (5.7) is run where the index option trading volume/open interest ratio is regressed on the FTSE100 returns and a dummy variable.

$$PCR_t^{TV,OI} = a + b_1 RFTSE_t + \ b_2 DUMRFTSE_t + \ e_t \qquad (5.7)$$

DUM = 1 if the previous number of consecutive days containing daily returns of the same sign is ≥3

DUM = 0 otherwise

The dummy variable approach will be repeated using trading volume/open interest of the portfolio of options written on financial stocks as the dependent variable and also returns on the financial stock portfolio to construct the explanatory variables.

5.5 Results

Table 5.6 Returns on FTSE100 and Trading Volume of FTSE100 Index Options

$$DFTSE_t = a + b_1 DFTSE_{t-1}\ \ b_2 PCR^{TV,OI}{}_{t-k} + \ e_t$$

Panel A: All Options

Entire Period					
Constant	**DFTSE(-1)**	**PCR_{TV}(-1)**	**PCR_{TV} (-7)**	**PCR_{TV} (-22)**	**R^2**
0.001339 (0.5118)	-0.081267** (0.0159)	-0.002263 (0.5139)			0.006377
-0.000203 (0.9151)	-0.077665** (0.0148)		0.000419 (0.8951)		0.006058
-0.001930 (0.3989)	-0.078491** (0.0141)			0.003427 (0.3638)	0.006774
Pre-Crisis					
Constant	**DFTSE(-1)**	**PCR_{TV} (-1)**	**PCR_{TV} (-7)**	**PCR_{TV} (-22)**	**R^2**
-0.002112 (0.6009)	0.038094 (0.7556)	0.004390 (0.4866)			0.004404
0.005608 (0.2148)	0.004801 (0.9681)		-0.008138 (0.2659)		0.014196
-0.005153 (0.2161)	-0.014005 (0.9001)			0.009395 (0.1324)	0.018044
Crisis					
Constant	**DFTSE(-1)**	**PCR_{TV} (-1)**	**PCR_{TV} (-7)**	**PCR_{TV} (-22)**	**R^2**
0.000755 (0.8721)	-0.102448** (0.0470)	-0.003159 (0.7038)			0.010051
0.001824 (0.6509)	-0.100985** (0.0320)		-0.005021 (0.4658)		0.010578
-0.006792 (0.1884)	-0.096521** (0.0386)			0.010120 (0.2310)	0.013266
Post-Crisis					
Constant	**DFTSE(-1)**	**PCR_{TV} (-1)**	**PCR_{TV} (-7)**	**PCR_{TV} (-22)**	**R^2**
0.004018 (0.1535)	-0.041202 (0.4299)	-0.006303 (0.2088)			0.003856
-0.002005 (0.4609)	-0.030819 (0.5318)		0.004816 (0.3132)		0.002664
-000221 (0.9420)	-0.030997 (0.5205)			0.001508 (0.7837)	0.001062

Panel B: Out-of-the-Money Options

Entire Period					
Constant	**RFTSE(-1)**	**PCR_{TV}(-1)**	**PCR_{TV} (-7)**	**PCR_{TV} (-22)**	**Adj R^2**
-5.317813 (0.6390)	-0.084005** (0.0048)	9.510348 (0.6021)			0.005842
-2.279699 (0.8191)	-0.084369* ((0.0051)		4.28172 (0.7913)		0.005542
-18.52252* (0.0623)	-0.084222*** (0.0050)			31.98667** (0.0447)	0.008489
Pre-Crisis					
Constant	**RFTSE(-1)**	**PCR_{TV} (-1)**	**PCR_{TV} (-7)**	**PCR_{TV} (-22)**	**Adj R^2**
-8.820682 (0.7065)	0.03455 (0.7579)	18.60816 (0.5891)			0.0016101
26.74199 (0.2759)	0.14723 (0.9008)		-36.9588 (0.3169)		0.009310
31.68030 (0.1172)	0.026002 (0.8204)			-44.93432 (0.1961)	0.004978
Crisis					
Constant	**RFTSE(-1)**	**PCR_{TV} (-1)**	**PCR_{TV} (-7)**	**PCR_{TV} (-22)**	**Adj R^2**
18.30971 (0.3858)	-0.116887** (0.0049)	-44.78893 (0.2376)			0.01219
-14.38665 (0.5027)	-0.117842* (0.0058)		14.110256 (0.7094)		0.009336
-38.34915 (0.0648)*	-0.114305*** (0.0065)			57.05958 (0.1026)	0.014263
Post-Crisis					
Constant	**RFTSE(-1)**	**PCR_{TV} (-1)**	**PCR_{TV} (-7)**	**PCR_{TV} (-22)**	**Adj R^2**
19.01555 (0.1178)	-0.00103 (0.9830)	-26.20833 (0.2233)			0.001726
11.17691 (0.4331)	0.001027 (0.9833)		-13.27592 (0.5815)		0.003927
-17.13928 (0.1899)	-0.006383 (0.8925)			37.77351* (0.0808)	0.001555

*Significant at the 10% level, ** at the 5% level, *** at the 1% level. Figures in parentheses are p-values.

The results presented in Table 5.6 provide support for the bulk of the literature, for example Stephan and Whaley (1990), in finding no significant relationship between FTSE100 returns and relative trading volume of FTSE100 index options using daily data. The only exceptions are for out-of-the-money options and a lag length of 22 days for the entire and post-crisis periods. Even in these cases the results are fairly weak. It is therefore reasonable to argue that the findings for the UK are broadly the same as those for CBOE options in the US and are robust throughout the recent financial crisis. For completeness the tests were also performed using a variety of lag lengths and with the first-difference of the trading volume ratio as the informational dependent variable. The results were not sensitive to these adjustments.

Table 5.7 Returns on FTSE100 and Open Interest of FTSE100 Index Options

Panel A: All Options

Entire Period					
Constant	**RFTSE(-1)**	**PCR_{OI} (-1)**	**PCR_{OI} (-7)**	**PCR_{OI} (-22)**	**Adj R^2**
-0.002224 (0.4713)	-0.071327** (0.0264)	-0.004023 (0.4594)			0.005451
-0.000768 (0.7423)	-0.071251** (0.0269)		0.001504 (0.7111)		0.005151
0.002595 (0.3515)	-0.071331** (0.0271)			-0.004749 (0.3378)	0.005531
Pre-Crisis					
Constant	**RFTSE(-1)**	**PCR_{OI} (-1)**	**PCR_{OI} (-7)**	**PCR_{OI} (-22)**	**Adj R^2**
-0.024985 (0.5576)	0.029219 (0.8036)	0.044609 (0.5463)			0.003212
0.030234 (0.4057)	0.028342 (0.8133)		-0.052139 (0.4131)		0.003723
0.058800 (0.3668)	0.026643 (0.8119)			-0.102472 (0.3734)	0.009232
Crisis					
Constant	**RFTSE(-1)**	**PCR_{OI} (-1)**	**PCR_{OI} (-7)**	**PCR_{OI} (-22)**	**Adj R^2**
0.005314 (0.8311)	-0.098198** (0.0371)	-0.011467 (0.7960)			0.009805
0.026846 (0.2627)	-0.100411** (0.0307)		-0.050537 (0.2375)		0.013161
0.026957 (0.2441)	-0.100230** (0.0330)			-0.050484 (0.2221)	0.012594
Post-Crisis					
Constant	**RFTSE(-1)**	**PCR_{OI} (-1)**	**PCR_{OI} (-7)**	**PCR_{OI} (-22)**	**Adj R^2**
0.001317 (0.6921)	-0.007010 (0.8869)	-0.001481 (0.8120)			0.000167
-0.003944* (0.0723)	-0.005493 (0.9117)		0.009053** (0.0257)		0.004276
0.001346 (0.6525)	-0.006881 (0.8894)			-0.001538 (0.7878)	0.000159

Panel B: Out-of-the-Money Options

Entire Period					
Constant	**RFTSE(-1)**	**PCR_{OI} (-1)**	**PCR_{OI} (-7)**	**PCR_{OI} (-22)**	**Adj R^2**
2.403239 (0.8500)	-0.084154*** (0.0069)	-3.544969 (0.8515)			0.005616
-2.787804 (0.8138)	-0.084658*** (0.0049)		4.929412 (0.7800)		0.005574
0.421426 (0.9689)	-0.084539*** (0.0050)			-0.426441 (0.9791)	0.005452
Pre-Crisis					
Constant	**RFTSE(-1)**	**PCR_{OI} (-1)**	**PCR_{OI} (-7)**	**PCR_{OI} (-22)**	**Adj R^2**
169.4642** (0.0068)	0.085092 (0.4519)	-230.4337*** (0.0071)			0.046732
13.43079 (0.8627)	0.029259 (0.7032)		-14.41068 (0.8931)		0.018486
32.18975 (0.6171)	0.025233 (0.8193)			-40.83420 (0.6586)	0.017528
Crisis					
Constant	**RFTSE(-1)**	**PCR_{OI} (-1)**	**PCR_{OI} (-7)**	**PCR_{OI} (-22)**	**Adj R^2**
10.05394 (0.6659)	-0.112334** (0.0124)	-32.02954 (0.4279)			0.010967
-4.036116 (0.8469)	-0.119068** (0.0048)		-4.907345 (0.8912)		0.009079
8.465655 (0.6486)	-0.120275*** (0.0044)			-28.27943 (0.3730)	0.010661
Post-Crisis					
Constant	**RFTSE(-1)**	**PCR_{OI} (-1)**	**PCR_{OI} (-7)**	**PCR_{OI} (-22)**	**Adj R^2**
9.705213 (0.5744)	0.000394 (0.9933)	-9.192034 (0.7321)			0.004341
11.49106 (0.4659)	-0.001835 (0.9697)		-12.18855 (0.6229)		0.004074
1.450677 (0.9201)	-0.001972 (0.9669)			4.609853 (0.8448	0.004588

*Significant at the 10% level, ** at the 5% level, *** at the 1% level. Figures in parentheses are p-values.

The results presented in table 5.7 indicate that relative open interest provides no significant indication of future returns on the underlying index when all options are included in the regressions. The put call ratio with a single lag is found to be significant and negative in the pre-crisis period when only out-of-the-money options are used. This indicates an increase in put open interest relative to that in calls prior to a fall in the index. One interpretation is that option investors are concerned about the possibility of a market fall and trade accordingly although this is an isolated result. The tests were also performed using a variety of lag lengths and with the first-difference of the open interest ratio as the informational dependent variable. The results were not sensitive to these adjustments.

Table 5.8 Returns on Portfolio of Individual Financial Stocks and FTSE100 Index Option Trading Volume

The regression in equation (5.3) is run again with the return on the financial stock portfolio replacing the FTSE100 as the dependent variable.

Panel A: All Options

Entire Period					
Constant	**RPort(-1)**	**PCR_{TV} (-1)**	**PCR_{TV} (-7)**	**PCR_{TV} (-22)**	**Adj R^2**
-0.002803 (0.5134)	0.012219 (0.7880)	0.004145 (0.5508)			0.000454
0.001121 (0.7675)	0.009147 (0.8314)		-0.002752 (0.6546)		0.000249
-0.000566 (0.8871)	0.009030 (0.8339)			0.000166 (0.9798)	0.000082
Pre-Crisis					
Constant	**RPort(-1)**	**PCR_{TV} (-1)**	**PCR_{TV} (-7)**	**PCR_{TV} (-22)**	**Adj R^2**
-0.005656 (0.2905)	0.084961 (0.4468)	0.009714 (0.2378)			0.015336
0.003550 (0.5650)	0.045853 (0.6654)		-0.005310 (0.5868)		0.006726
-0.007350 (0.1638)	0.024780 (0.7950)			0.012465 (0.1176)	0.022298
Crisis					
Constant	**RPort(-1)**	**PCR_{TV} (-1)**	**PCR_{TV} (-7)**	**PCR_{TV} (-22)**	**Adj R^2**
-0.005130 (0.4776)	-0.005261 (0.9207)	0.004686 (0.7116)			0.000433
0.000937 (0.8898)	-0.10400 (0.8347)		-0.006026 (0.6025)		0.000680
-0.011065 (0.1030)	-0.008355 (0.8641)			0.015062 (0.1847)	0.003790
Post-Crisis					
Constant	**RPort(-1)**	**PCR_{TV} (-1)**	**PCR_{TV} (-7)**	**PCR_{TV} (-22)**	**Adj R^2**
0.001576 (0.8485)	0.025812 (0.7502)	-0.002117 (0.8780)			0.000801
0.002281 (0.7261)	0.027680 (0.7143)		-0.003445 (0.7544)		0.000920
0.005981 (0.4329)	0.028031 (0.7108)			-0.010323 (0.4458)	0.002414

Panel B: Out-of-the-Money

Entire Period					
Constant	**RPort(-1)**	**PCR_{TV} (-1)**	**PCR_{TV} (-7)**	**PCR_{TV} (-22)**	**Adj R^2**
0.000901 (0.8243)	0.020406 (0.6418)	-0.002074 (0.7486)			0.001143
0.000631 (0.8635)	0.020373 (0.6427)		-0.00164 (0.7748)		0.001189
-0.0017 (0.5874)	0.020729 (0.6360)			0.002295 (0.6489)	0.001139
Pre-Crisis					
Constant	**RPort(-1)**	**PCR_{TV} (-1)**	**PCR_{TV} (-7)**	**PCR_{TV} (-22)**	**Adj R^2**
-0.007910 (0.0985)	0.062860 (0.5693)	0.012449* (0.0649)			0.011978
0.001559 (0.7743)	0.053211 (0.6322)		-0.002403 (0.7658)		0.015334
0.006365* (0.0763)	0.055558 (0.5942)			-0.009957 (0.1102)	0.000124
Crisis					
Constant	**RPort(-1)**	**PCR_{TV} (-1)**	**PCR_{TV} (-7)**	**PCR_{TV} (-22)**	**Adj R^2**
0.004526 (0.4751)	0.005879 (0.9090)	-0.012098 (0.2979)			0.003017
-0.004677 (0.5021)	0.004018 (0.9391)		0.004324 (0.7159)		0.005189
-0.010672* (0.0744)	0.003224 (0.9498)	0.003224 (0.9498)		0.014886 (0.1629)	0.001696
Post-Crisis					
Constant	**RPort(-1)**	**PCR_{TV} (-1)**	**PCR_{TV} (-7)**	**PCR_{TV} (-22)**	**Adj R^2**
0.003672 (0.6463)	0.035351 (0.6487)	-0.005757 (0.6559)			0.002201
0.005604 (0.3953)	0.032221 (0.6799)		-0.009208 (0.3882)		0.001087
0.002801 (0.6045)	0.035213 (0.6410)			-0.004223 (0.6468)	0.002522

*Significant at the 10% level, ** at the 5% level, *** at the 1% level. Figures in parentheses are p-values.

Only one of the coefficients in Table 5.8, the put to call ratio with one lag, is found to be statistically significant. Even then the relationship is very weak. Hence it is not possible to infer any return predictability from FTSE100 index trading volume on the portfolio of financial stocks in the crisis period or sub-periods.

Table 5.9 Returns on Portfolio of Individual Financial Stocks and FTSE100 Index Option Open Interest

Panel A: All Options

Entire Period					
Constant	**RPort(-1)**	**PCR_{OI}(-1)**	**PCR_{OI} (-7)**	**PCR_{OI} (-22)**	**Adj R^2**
0.001860 (0.6659)	0.009211 (0.8308)	-0.004280 (0.5591)			0.000226
0.005357 (0.1704)	0.009069 (0.8332)		-0.010788 (0.1030)		0.000998
0.003256 (0.4550)	0.009036 (0.8343)			-0.006910 (0.3555)	0.000459
Pre-Crisis					
Constant	**RPort(-1)**	**PCR_{OI}(-1)**	**PCR_{OI} (-7)**	**PCR_{OI} (-22)**	**Adj R^2**
-0.030514 (0.5887)	0.058508 (0.5667)	0.053690 (0.5840)			0.00503
0.074945 (0.2092)	0.050679 (0.6088)		-0.131220 (0.2131)		0.014126
0.107107 (0.2347)	0.040481 (0.6480)			-0.188017 (0.2382)	0.020263
Crisis					
Constant	**RPort(-1)**	**PCR_{OI}(-1)**	**PCR_{OI} (-7)**	**PCR_{OI} (-22)**	**Adj R^2**
-0.024111 (0.5587)	-0.011055 (0.8276)	0.039286 (0.5921)			0.001097
0.005874 (0.8878)	-0.009759 (0.8453)		-0.015172 (0.8378)		0.000245
-0.010008 (0.8040)	-0.009839 (0.8444)			0.013570 (0.8497)	0.000193
Post-Crisis					
Constant	**RPort(-1)**	**PCR_{OI}(-1)**	**PCR_{OI} (-7)**	**PCR_{OI} (-22)**	**Adj R^2**
0.002506 (0.5443)	0.027470 (0.7185)	-0.004161 (0.6048)			0.000925
0.006584 (0.0854)	0.028419 (0.7084)		-0.012320 (0.1038)		0.002398
0.004118 (0.3944)	0.027044 (0.7233)			-0.007383 (0.4183)	0.001256

Panel B: Out-of-the-Money Options

Entire Period					
Constant	**RPort(-1)**	**PCR_{OI}(-1)**	**PCR_{OI} (-7)**	**PCR_{OI} (-22)**	**Adj R^2**
-0.000906 (0.8604)	0.020049 (0.6408)	0.020049 (0.6404)			0.001234
-0.001284 (0.7977)	0.020396 (0.6381)		0.001565 (0.8311)		0.001182
-0.005158 (0.3530)	0.018520 (0.6599)			0.007868 (0.3399)	0.000709
Pre-Crisis					
Constant	**RPort(-1)**	**PCR_{OI}(-1)**	**PCR_{OI} (-7)**	**PCR_{OI} (-22)**	**Adj R^2**
0.028208** (0.0464)	0.102423 (0.3163)	-0.039057** (0.0419)			0.01753
-0.006039 (0.7485)	0.069482 (0.5674)		0.008437 (0.7454)		0.014734
0.008389 (0.6266)	0.054235 (0.5999)			-0.011765 (0.6371)	0.013999
Crisis					
Constant	**RPort(-1)**	**PCR_{OI}(-1)**	**PCR_{OI} (-7)**	**PCR_{OI} (-22)**	**Adj R^2**
-0.000235 (0.9696)	0.005311 (0.9179)	-0.003764			0.005239
-0.002631 (0.6760)	0.004939 (0.9238)		0.000702 (0.9453)		0.005506
-0.007007 (0.3875)	0.004218 (0.9352)			0.008435 (0.5094)	0.004277
Post-Crisis					
Constant	**RPort(-1)**	**PCR_{OI}(-1)**	**PCR_{OI} (-7)**	**PCR_{OI} (-22)**	**Adj R^2**
0.001223 (0.9041)	0.036081 (0.6340)	-0.001290 (0.9339)			0.002917
0.002199 (0.8137)	0.036183 (0.6375)		-0.003046 (0.8312)		0.002681
-0.004728 (0.5909)	0.033361 (0.6376)			0.009168 (0.5055)	0.000435

*Significant at the 10% level, ** at the 5% level, *** at the 1% level. Figures in parentheses are p-values.

None of the coefficients in the results presented in Table 5.9, Panel A are statistically significant. In Panel B the coefficient for 1 lag of the put to call open interest ratio is significant and negative for the pre-crisis period. This can be interpreted as limited evidence of return predictability in financial stocks from index option open interest prior to the crisis period. However, in aggregate the hypothesis that daily lagged relative trading volume and open interest from equity options has no explanatory power for returns on the underlying equity portfolio during the period 2006-2010 nor in any of the sub-periods cannot be rejected.

The regression in equation (5.3) is run again with the trading volume ratio and then the open interest ratio of the related equity option contracts employed as the explanatory variable.

Table 5.10 Returns on Portfolio of Individual Financial Stocks and Equity Option Trading Volume

Panel A: All Options

Entire Period					
Constant	**RPort(-1)**	**PCR_{TV} (-1)**	**PCR_{TV} (-7)**	**PCR_{TV} (-22)**	**Adj R^2**
-0.002984 (0.6612)	0.021262 (0.6325)	0.003042 (0.6834)			0.000560
0.001945 (0.7948)	0.020486 (0.6417)		-0.002577 (0.7528)		0.000526
0.007095 (0.2420)	0.20022 (0.6455)			-0.008433 (0.2189)	0.001508
Pre-Crisis					
Constant	**RPort(-1)**	**PCR_{TV} (-1)**	**PCR_{TV} (-7)**	**PCR_{TV} (-22)**	**Adj R^2**
-0.075392 (0.5590)	0.059708 (0.5558)	0.076337 (0.5569)			0.005390
0.035331 (0.6290)	0.050378 (0.6247)		-0.035512 (0.6313)		0.004518
0.006759 (0.5959)	0.052250 (0.6069)			-0.006688 (0.6627)	0.003425
Crisis					
Constant	**RPort(-1)**	**PCR_{TV} (-1)**	**PCR_{TV} (-7)**	**PCR_{TV} (-22)**	**Adj R^2**
-0.038538 (0.3532)	0.01057 (0.8451)	0.037581 (0.3802)			0.001721
-0.034666 (0.3585)	0.004002 (0.9399)		0.33511 (0.3854)		0.001400
-0.035889 (0.3635)	0.003692 (0.9447)			0.034755 (0.3893)	0.001543
Post-Crisis					
Constant	**RPort(-1)**	**PCR_{TV} (-1)**	**PCR_{TV} (-7)**	**PCR_{TV} (-22)**	**Adj R^2**
-0.077648*** (0.0011)	0.051742 (0.4486)	0.100893*** (0.00009)			0.030301
-0.026969 (0.2462)	0.027341 (0.7012)		0.035422 (0.2308)		0.005364
0.006197 (0.8514)	0.033801 (0.6529)			-0.007183 (0.8677)	0.001358

Panel B: Out-of-the-Money Options

Entire Period					
Constant	**RPort(-1)**	**PCR_{TV} (-1)**	**PCR_{TV} (-7)**	**PCR_{TV} (-22)**	**Adj R^2**
0.001249 (0.5915)	0.018092 (0.6797)	-0.002942 (0.4391)			0.000738
0.000937 (0.7064)	0.020380 (0.6441)		-0.002386 (0.5852)		0.000917
0.000458 (0.8261)	0.020382 (0.6435)			0.001542 (0.6576)	0.001138
Pre-Crisis					
Constant	**RPort(-1)**	**PCR_{TV} (-1)**	**PCR_{TV} (-7)**	**PCR_{TV} (-22)**	**Adj R^2**
0.000920 (0.7378)	0.062028 (0.5511)	-0.001727 (0.7090)			0.014845
0.000447 (0.8225)	0.056973 (0.5919)		-0.000808 (0.8290)		0.015953
-0.004166 (0.1051)	0.044609 (0.6121)			0.008116* (0.0501)	0.010774
Crisis					
Constant	**RPort(-1)**	**PCR_{TV} (-1)**	**PCR_{TV} (-7)**	**PCR_{TV} (-22)**	**Adj R^2**
0.004833 (0.3405)	-0.006921 (0.8896)	-0.013144 (0.1052)			0.001223
0.001282 (0.7750)	0.004076 (0.9372)		-0.006509 (0.4085)		0.003820
0.006013 (0.1858)	-0.002222 (0.9650)			-0.015127* (0.0515)	0.003213
Post-Crisis					
Constant	**RPort(-1)**	**PCR_{TV} (-1)**	**PCR_{TV} (-7)**	**PCR_{TV} (-22)**	**Adj R^2**
-0.002043 (0.6806)	0.038935 (0.6053)	0.004567 (0.5670)			0.002025
0.001096 (0.8497)	0.036539 (0.6268)		-0.001219 (0.9003)		0.002857
-0.002939 (0.4912)	0.035104 (0.6368)			0.006294 (0.3496)	0.001117

*Significant at the 10% level, ** at the 5% level, *** at the 1% level. Figures in parentheses are p-values.

The results presented in Table 5.10 are mostly insignificant. In Panel A, only relative trading volume lagged by one day during the crisis period is statistically significant and even in this case the value of the R-squared statistic is very low. In Panel B, the put to call ratio with 22 lags is significant with 22 lags. The relationship is positive in the pre-crisis period and negative in the crisis period suggesting that little can be inferred in terms of predictability. The tests were also run with 2 and 3 lags but no statistically significant coefficients were produced. Furthermore, the results are insensitive to using the first-difference of the trading volume or open interest ratio as the informational explanatory variable. A statistically significant but small relationship is found when contemporaneous trading volume is used.

Table 5.11 Returns on Portfolio of Individual Financial Stocks and Equity Option Open Interest

Panel A: All Options

Entire Period					
Constant	**RPort(-1)**	**PCR_{OI} (-1)**	**PCR_{OI} (-7)**	**PCR_{OI} (-22)**	**Adj R^2**
0.003678 (0.1681)	0.018619 (0.5197)	-0.00571 (0.1209)			0.002428
0.002949 (0.2716)	0.019079 (0.5106)		-0.004570 (0.2050)		0.01773
0.005319** (0.0497)	0.017168 (0.5559)			-0.007886** (0.0301)	0.004417
Pre-Crisis					
Constant	**RPort(-1)**	**PCR_{OI} (-1)**	**PCR_{OI} (-7)**	**PCR_{OI} (-22)**	**Adj R^2**
0.032900 (0.1101)	0.058180 (0.5552)	-0.033080 (0.1122)			0.027548
-0.001215 (0.8780)	0.053339 (0.5930)		0.001502 (0.8543)		0.003158
0.001447 (0.7789)	0.052566 (0.5984)			-0.00134 (0.8099)	0.003397
Crisis					
Constant	**RPort(-1)**	**PCR_{OI} (-1)**	**PCR_{OI} (-7)**	**PCR_{OI} (-22)**	**Adj R^2**
-0.003906 (0.9142)	0.006549 (0.8984)	0.001504 (0.9680)			0.000049
-0.049006 (0.2373)	0.003943 (0.9403)		0.048617 (0.2613)		0.003539
-0.006173 (0.8590)	0.006396 (0.9028)			0.003868 (0.9137)	0.000068
Post-Crisis					
Constant	**RPort(-1)**	**PCR_{OI} (-1)**	**PCR_{OI} (-7)**	**PCR_{OI} (-22)**	**Adj R^2**
-0.053959** (0.0321)	0.029801 (0.6857)	0.098710** (0.0270)			0.006325
-0.013653* (0.0905)	0.031217 (0.6764)		0.025504* (0.0657)		0.003282
0.016746 (0.4491)	0.028835 (0.6378)			-0.028426 (0.4769)	0.008395

Panel B: Out-of-the-Money Options

Entire Period					
Constant	**RPort(-1)**	**PCR_{OI} (-1)**	**PCR_{OI} (-7)**	**PCR_{OI} (-22)**	**Adj R^2**
-0.003711 (0.3284)	0.025302 (0.5514)	0.007302 (0.4167)			0.000280
-0.002147 (0.5645)	0.01981 (0.6584)		0.00391 (0.6566)		
-0.002103 (0.5713)	0.020281 (0.6490)			0.00376 (0.6654)	0.000871
Pre-Crisis					
Constant	**RPort(-1)**	**PCR_{OI} (-1)**	**PCR_{OI} (-7)**	**PCR_{OI} (-22)**	**Adj R^2**
-0.017441 (0.0648)	0.10838 (0.3046)	0.040387* (0.0679)			0.017458
0.006646 (0.5349)	0.060529) (0.5715)		-0.015398 (0.5370)		0.010266
0.002442 (0.7105)	0.058754 (0.5726)			-0.005715 (0.7017)	0.015227
Crisis					
Constant	**RPort(-1)**	**PCR_{OI} (-1)**	**PCR_{OI} (-7)**	**PCR_{OI} (-22)**	**Adj R^2**
-0.019391*** (0.0056)	0.016374 (0.7441)	0.034714** (0.0169)			0.014421
-0.010663 (0.1430)	-0.00235 (0.9658)		0.017171 (0.2398)		0.000945
-0.011704 (0.1682)	-0.000732 (0.9891)			0.019866 (0.2372)	0.000732
Post-Crisis					
Constant	**RPort(-1)**	**PCR_{OI} (-1)**	**PCR_{OI} (-7)**	**PCR_{OI} (-22)**	**Adj R^2**
0.000530 (0.9396)	0.036169 (0.6074)	-0.000178 (0.9908)			0.002921
-0.001339 (0.8409)	0.036058 (0.6386)		0.003435 (0.8160)		0.002606
-0.00008 (0.9891)	0.036344 (0.6310)			0.000994 (0.9399)	0.002893

*Significant at the 10% level, ** at the 5% level, *** at the 1% level. Figures in parentheses are p-values.

The results in Table 5.11 show few significant coefficients; four in total, evenly split between Panels A and B and with no consistency in time. Once again there is little evidence of return predictability for the equity portfolio provided by equity option open interest.

The results presented in the preceding tables provide a clear rejection of the hypothesis that relative trading volume and open interest provide information on spot market returns when daily data is analysed. Nevertheless the results provide some support to the argument of Pan and Poteshman (2006) that trading volume and open interest data for out-of-the-money options contain more information than is contained in the trading volume and open interest data in aggregate. Consequently it cannot be inferred that any trading information can be gathered by analysing lagged trading volume or lagged open interest that will be useful in achieving abnormal returns. These results are insensitive to the selection of sample period across the duration of the recent financial crisis and are consistent with the efficient markets hypothesis.

Modelling the Contemporaneous Relationship between Equity Returns, Trading Volume and Open Interest

The results presented in Tables 5.12 to 5.15 are produced by running the regressions given in equations (5.5) and (5.6). The contemporaneous relationship between returns on the financial portfolio and corresponding trading volume and open interest ratios is examined, with no initial assumption regarding the direction. The hypothesis to be tested is that there is a price discovery relationship between returns on the portfolio of financial stocks and the trading volume and open interest of options written on those stocks.

Table 5.12 Returns on Financial Portfolio and Trading Volume

Dependant variable is the portfolio return:

Panel A: All Options

Entire Period			
Constant	**RPort(-1)**	**PCR_{TV}**	**Adj R^2**
0.015463* (0.0652)	0.017146 (0.7058)	-0.017146* (0.0506)	0.005439
Pre-Crisis			
Constant	**RPort(-1)**	**PCR_{TV}**	**Adj R^2**
0.175229 (0.3906)	0.035016 (0.7546)	-0.176656 (0.3904)	0.016491
Crisis			
Constant	**RPort(-1)**	**PCR_{TV}**	**Adj R^2**
0.077003 (0.1012)	0.007166 (0.8896)	-0.082776* (0.0873)	0.008229
Post-Crisis			
Constant	**RPort(-1)**	**PCR_{TV}**	**Adj R^2**
0.051677 (0.1064)	0.028515 (0.7151)	-0.065957 (0.1021)	0.013255

Panel B: Out-of-the-Money Options

Entire Period			
Constant	**RPort(-1)**	**PCR_{TV}**	**Adj R^2**
0.006464*** (0.0010)	0.018634 (0.6717)	-0.012766*** (0.0001)	0.008670
Pre-Crisis			
Constant	**RPort(-1)**	**PCR_{TV}**	**Adj R^2**
-0.001835 (0.4525)	0.065775 (0.5345)	0.003604 (0.3446)	0.010280
Crisis			
Constant	**RPort(-1)**	**PCR_{TV}**	**Adj R^2**
0.009911** (0.0344)	-0.007281 (0.8906)	-0.022559*** (0.0034)	0.014743
Post-Crisis			
Constant	**RPort(-1)**	**PCR_{TV}**	**Adj R^2**
0.008109** (0.0331)	0.041064 (0.5853)	-0.014097 (0.0186)	0.005655

*Significant at the 10% level, ** at the 5% level, *** at the 1% level. Figures in parentheses are p-values.

In Panel A, the signs attached to the trading volume ratio are all negative indicating the expected result that negative returns on the equity portfolio are linked contemporaneously with increases in the trading volume ratio. However the relationship is only statistically significant over the entire period and the crisis period with the associated R-squared statistics weak in each case. In Panel B the relationship is the same but significant at the 1% level. This result suggests the possibility of a weak price discovery relationship particularly when the trading volume of out-of-the-money put options is examined.

Table 5.13 Returns on Financial Portfolio and Trading Volume

Dependant Variable is the Trading Volume Ratio.

Panel A: All Options

Entire Period			
Constant	**RPort**	**RPort(-1)**	**R^2**
0.879722*** (0.0000)	-0.282891* (0.0520)		0.005108
0.879701*** (0.0000)		-0.1811538 (0.1391)	0.002104
Pre-Crisis			
Constant	**RPort**	**RPort(-1)**	**R^2**
0.990634*** (0.0000)	-0.082829 (0.3823)		0.015296
0.990633 (0.0000)		-0.102895* (0.0875)	0.023551
Crisis			
Constant	**RPort**	**RPort(-1)**	**R^2**
0.959796 (0.1024)	-0.098825 (0.1024)		0.008177
0.960054*** (0.0000)		0.005102 (0.9189)	0.000022
Post-Crisis			
Constant	**RPort**	**RPort(-1)**	**R^2**
0.774928 (0.0000)	-0.186464 (0.1010)		0.012444
0.774865*** (0.0000)		-0.076132 (0.3350)	0.002074

Panel B: Out-of-the-Money Options

Entire Period			
Constant	**RPort**	**RPort(-1)**	**R^2**
0.530527*** (0.0000)	-0.778918*** (0.0009)		0.009973
0.530714*** (0.0000)		-0.136211 (0.5154)	0.000305
Pre-Crisis			
Constant	**RPort**	**RPort(-1)**	**R^2**
0.515786*** (0.0000)	1.520053 (0.3851)		0.005120
0.516014*** (0.0000)		-1.652115 (0.3857)	0.005930
Crisis			
Constant	**RPort**	**RPort(-1)**	**R^2**
0.538278*** (0.0000)	-0.895759** (0.0156)		0.020119
0.539076*** (0.0000)		-0.542153* (0.0676)	0.004629
Post-Crisis			
Constant	**RPort**	**RPort(-1)**	**R^2**
0.544532*** (0.0000)	-0.593570** (0.0472)		0.008177
0.544113*** (0.0000)		0.336914 (0.2118)	0.000522

*Significant at the 10% level, ** at the 5% level, *** at the 1% level. Figures in parentheses are p-values.

The results in Panel A indicate that, over the entire period there is a significant negative impact of equity portfolio return on the trading volume ratio. There is also a significant negative impact of lagged portfolio return during the pre-crisis period. The signs on all but the lagged portfolio in the crisis period are negative as expected. In Panel B there is a significant and negative impact of equity portfolio return on the trading volume ratio in all but the pre-crisis period. This relationship extends to the lagged return on the equity portfolio over the crisis period. It seems just as likely that trading volume reacts to stock returns rather than price discovery information flowing in the opposite direction.

Table 5.14 Returns on Financial Portfolio and Open Interest

Dependant variable is the portfolio return:

Panel A: All Options

Entire Period			
Constant	**RPort(-1)**	**PCR_{OI}**	**Adj R^2**
0.003100 (0.2381)	0.018829 (0.6719)	-0.004764 (0.1662)	0.001887
Pre-Crisis			
Constant	**RPort(-1)**	**PCR_{OI}**	**Adj R^2**
-0.190039 (0.2591)	0.048439 (0.6115)	-0.191775 (0.2573)	0.016426
Crisis			
Constant	**RPort(-1)**	**PCR_{OI}**	**Adj R^2**
-0.087581** (0.0260)	-0.004900 (0.9263)	-0.088930** (0.0281)	0.011484
Post-Crisis			
Constant	**RPort(-1)**	**PCR_{OI}**	**Adj R^2**
-0.345265* (0.0625)	0.017917 (0.7835)	-0.627054* (0.0608)	0.018125

Panel B: Out-of-the-Money Options

Entire Period			
Constant	**RPort(-1)**	**PCR_{OI}**	**Adj R^2**
0.010361*** (0.0084)	0.005688 (0.8869)	-0.022902** (0,0145)	0.013903
Pre-Crisis			
Constant	**RPort(-1)**	**PCR_{OI}**	**Adj R^2**
0.024201* (0.0761)	-0.011383 (0.9128)	-0.055869 (0.0928)	0.047215
Crisis			
Constant	**RPort(-1)**	**PCR_{OI}**	**Adj R^2**
0.007820 (0.2801)	-0.000471 (0.9930)	-0.020356 (0.1873)	0.001406
Post-Crisis			
Constant	**RPort(-1)**	**PCR_{OI}**	**Adj R^2**
0.016397** ((0.0314)	0.011087 (0.8625)	-0.030961* (0.0624)	0.021261

*Significant at the 10% level, ** at the 5% level, *** at the 1% level. Figures in parentheses are p-values.

The signs of the coefficients attached to the open interest ratio in each case are negative as expected indicating that falling index returns are associated with an increase in the number of open positions in put options on financial stocks at the close of each trading day. The coefficients are statistically significant for the crisis and post-crisis period in Panel A and the entire and post-crisis periods in Panel B. These results provide some evidence that the relationship has changed over the recent financial crisis. It is not possible to reject a contemporaneous impact of open interest on the financial stock portfolio returns indicating fairly weak price discovery.

Table 5.15 Returns on Financial Portfolio and Open Interest

Dependant variable is the open interest ratio

Panel A: All Options

Entire Period			
Constant	**RPort**	**RPort(-1)**	**R^2**
0.715148*** (0.0000)	-0.317947 (0.1635)		0.001557
0.715292*** (0.0000)		-0.329773 (0.1499)	0.001676
Pre-Crisis			
Constant	**RPort**	**RPort(-1)**	**R^2**
0.992128*** (0.0000)	0.072247 (0.1993)		0.014089
0.992140*** (0.0000)		0.024787 (0.7721)	0.001655
Crisis			
Constant	**RPort**	**RPort(-1)**	**R^2**
0.917544*** (0.0000)	0.360913 (0.3000)		0.835438
0.917643*** (0.0000)		0.383181 (0.2751)	0.009839
Post-Crisis			
Constant	**RPort**	**RPort(-1)**	**R^2**
0.551521*** (0.0000)	0.027947** (0.0424)		0.017808
0.551522*** (0.0000)		0.024910* (0.0686)	0.014149

Panel B: Out-of-the-Money Options

Entire Period			
Constant	**RPort**	**RPort(-1)**	**R^2**
0.465842*** (0.0000)	-0.676176** (0.0127)		0.015606
0.465985*** (0.000)		-0.641236 (0.0215)	0.014049
Pre-Crisis			
Constant	**RPort**	**RPort(-1)**	**R^2**
0.432625*** (0.0000)	-1.188191* (0.0533)		0.065598
0.432727*** (0.0000)		-1.274474* (0.0507)	0.074000
Crisis			
Constant	**RPort**	**RPort(-1)**	**R^2**
0.494558*** (0.0000)	-0.339464 (0.1597)		0.006908
0.494722*** (0.0000)		-0.266254 (0.2612)	0.004250
Post-Crisis			
Constant	**RPort**	**RPort(-1)**	**R^2**
0.515435*** (0.0000)	-0.807342* (0.0565)		0.025279
0.515429*** (0.0000)		-0.814805* (0.0623)	0.025757

*Significant at the 10% level, ** at the 5% level, *** at the 1% level. Figures in parentheses are p-values.

In Panel A, although for the entire period the signs on the coefficients attached to the dependent variables are negative they are positive for each sub-period. However the coefficients for all periods other than the post-crisis are not statistically significant. Hence it is not possible to infer any consistent relationship between contemporaneous and lagged stock returns and open interest using the aggregate open interest of the equity options. In Panel B, the coefficients attached to portfolio returns in the entire, pre-crisis and post-crises periods are negative and significant. It follows that, when only out-of-the-money options are examined, there is evidence that trading volume and open interest react to returns on the underlying assets.

5.6 A Behavioural Perspective on Trading Volume and Open Interest

In this section it is hypothesised that trading behaviour in the UK market occurs as a rational response to spot market activity as traders update their beliefs regarding risk in accordance with the direction and magnitude of market returns. If this is the case then total trading volume should increase (decrease) with negative (positive) returns that are contemporaneous or lagged by one day. It is unlikely that lagged returns of more than one day will have a significant effect on trading volume. However, from a behavioural perspective a series of returns of the same sign may lead conservative traders to perceive this to be a trend and to update their beliefs accordingly. A consequence would be that a series of negative returns would lead to an increase in put purchases relative to calls and vice versa. Table 5.16 presents the results from running equation (5.7) where the index option trading volume ratio is regressed on the FTSE100 returns and a dummy variable. The dummy variable is equal to 1 if three or more of the consecutive preceding FTSE100 returns are of the same sign and zero otherwise. Tests are run for the entire period only, as the clustering of runs of positive and negative returns is likely to bias the results for sub-periods.

Table 5.16 Contemporaneous Returns and Trends in Return Innovations: FTSE100 Index Returns and Index Option Trading Volume and Open Interest

$$PCR_t^{TV,OI} = a + b_1 RFTSE_t + b_2 DUMRFTSE_t + e_t$$

Panel A: All Options

Trading Volume Ratio			
Constant	**RFTSE**	**DUM**	**Adj R^2**
0.576210*** (0.0000)	-1.523324*** (0.0000)	-0.019586** (0.0252)	0.040525
Open Interest Ratio			
0.541478*** (0.0000)	0.007260 (0.9362)	-0.009737* (0.0748)	0.003188

Panel B: Out-of-the-money Options

Trading Volume Ratio			
Constant	**RFTSE**	**DUM**	**Adj R^2**
0.584118*** (0.0000)	-0.00005*** (0.0000)	-1.664994*** (0.0055)	0.005278
Open Interest Ratio			
0.611176*** (0.0000)	0.000248*** (0.0000)	2.539909*** (0.0001)	0.030382

*Significant at the 10% level, ** at the 5% level, *** at the 1% level. Figures in parentheses are p-values.

The coefficient attached to the FTSE100 returns is significant and negative indicating that relative trading volume rises (falls) with negative (positive) contemporaneous spot market returns. The coefficient attached to the dummy variable is negative and significant indicating that a series of lagged negative or positive returns also leads to increases in relative trading volume. The effect is relatively weak in Panel A but stronger and more significant in Panel B. There is also a significant coefficient attached to the dummy variable when the dependent variable is open interest in Panel A although the impact of the contemporaneous index returns is not significant. Both coefficients are significant in Panel B however open interest is found to be positively related to runs of returns on the FTSE100 of the same sign.

The observation that the results are strongest in Panel B can be interpreted as options investors turning to out-of-the-money options following an upward or downward trend. The negative coefficient attached to the dummy variable regressed on the trading volume ratio can be interpreted as investors trading more put (call) options than call (put) options following a consecutive 3-day negative (positive) run. The positive coefficient attached to the dummy variable regressed on the open interest ratio is more difficult to rationalise. The implication is that more put (call) positions are closed out relative to call (put) positions in a falling (rising) market. As the options are European-style no early exercise can take place. It follows that a change in the open interest ratio is as a result of options being either written or closed out by taking offsetting positions. Another point to note is that open interest will contain option positions that remain open for a period of time but have no trading volume. A run of stock market rises (falls) results in more calls (puts) ceasing to be out-of-the-money. This means that they exit the out-of-the-money data set whilst the corresponding, previously in-the-money options of the other category enter. Should there be a sharp rise or fall in the underlying market, this will result in a considerable impact on the size of the open interest ratio.

A further test is performed to establish the impact of returns on the portfolio of financial stocks on the trading volume and open interest ratios with results presented in Table 5.17.

Table 5.17 Contemporaneous Returns and Trends in Return Innovations: FTSE100 Index Returns and Equity Option Trading Volume and Open Interest

Panel A: All Options

Trading Volume Ratio (FTSE100)			
Constant	**RPORT**	**DUMPORT**	**Adj R^2**
0.571569*** (0.0000)	-0.611189*** (0.0007)	-1.930441*** (0.0071)	0.038595
Open Interest Ratio (FTSE100)			
0.539298*** (0.0000)	0.074523 (0.2349)	-0.334059 (0.1488)	0.001038

Panel B: Out-of-the-money Options

Trading Volume Ratio (FTSE100)			
Constant	**RPORT**	**DUMPORT**	**Adj R^2**
0.584375 (0.0000)	0.00039 (0.4346)	0.216255 (0.4647)	0.000734
Open Interest Ratio			
0.612066*** (0.0000)	0.000266*** (0.0000)	1.084331*** (0.0007)	0.027245

*Significant at the 10% level, ** at the 5% level, *** at the 1% level. Figures in parentheses are p-values.

The results presented in Table 5.17, Panel A are similar to those in Table 5.16 when the trading volume ratio is the dependent variable. The coefficient attached to the equity portfolio returns is significant and negative indicating that relative trading volume rises (falls) with negative (positive) contemporaneous returns on a portfolio of financial stocks. The coefficient attached to the dummy variable is negative and significant indicating that a series of negative or positive returns also leads to increases in relative trading volume. A significant but weak coefficient is attached to the dummy when open interest is the dependent variable. In Panel B, a positive and significant coefficient is again observed which is consistent with the observation in table 5.17. As the individual equity options are American-style one possible interpretation is that option traders display a disposition effect. This implies that the holders of options realise gains by early exercising options that move into (or deeper into) the money following a series of consecutive price changes in the underlying asset. This explanation is consistent with options being held for speculative rather than hedging purposes. However, the explanation offered is impossible to support without precise information on the type of trades that take place on each trading day.

To complete this section of the analysis the trading volume and open interest ratios of the equity portfolio will be regressed on the contemporaneous equity portfolio returns and a dummy variable for the equity portfolio which is constructed in the same way as that for the FTSE100.

Table 5.18 Contemporaneous Returns and Trends in Return Innovations: Equity Portfolio Returns and Equity Option Trading Volume and Open Interest

Trading Volume Ratio (Equity Port)			
Constant	**RPORT**	**DUMPORT**	**Adj R^2**
0.954329*** (0.0000)	-0.027861 (0.8885)	-1.485778*** (0.0002)	0.028537
Open Interest Ratio (Equity Port)			
0.776168*** (0.0000)	-0.055089 (0.9493)	-3.263313** (0.0327)	0.010036

Panel B: Out-of-the-money Options

Trading Volume Ratio (Equity Port)			
Constant	**RPORT**	**DUMPORT**	**Adj R^2**
0.530322*** (0.0000)	0.000048 (0.5248)	0.166560 (0.7066)	0.001227
Open Interest Ratio			
0.464168*** (0.0000)	-0.000131** (0.0104)	-1.820266*** (0.0000)	0.032729

*Significant at the 10% level, ** at the 5% level, *** at the 1% level. Figures in parentheses are p-values.

The results in Table 5.18, Panel A indicate no significant relationship between contemporaneous equity portfolio returns and the respective trading volume and open interest ratios. There is however a significant negative relationship between the dummy variable and each dependent variable. This result indicates that a run of positive (negative) returns of the same sign is associated with a decrease (increase) in relative trading volume and open interest. In Panel B, both coefficients are insignificant for the trading volume ratio. Interestingly, the coefficient attached to the dummy variable for equity portfolio returns is negative in contrast to that in Tables 5.17 and 5.18. This does however support the hypothesis that open interest of puts rises relative to that of calls following a run of consecutive daily stock returns of the same sign.

The findings in this section are consistent with the behavioural models of Barberis, Shleifer and Vishny (1998) in the equity market and Poteshman (2001) in the options market which were discussed in detail in Chapter 2. Options market traders seem to display conservatism in their trading behaviour in response to returns in the aggregate and individual equity markets. Conversely, when these returns follow a consecutive series of innovations of the same sign, investors demonstrate representativeness by perceiving this as a trend and modify their trading behaviour accordingly.

5.7 Conclusion

The results presented above clearly indicate that there is no evidence of stock market predictability in daily trading volume and open interest data from the UK exchange-traded options market. This implies that published options market information cannot be used by investors to construct profitable trading strategies. This does not necessarily imply that particular categories of trader are not privy to private information, as the Euronext LIFFE data cannot be disaggregated for the purposes of such an examination. The rejection of predictability may not be interpreted as an automatic rejection of a price discovery function. Price discovery will be a consequence of the trades of sophisticated investors with access to private information. These findings are consistent with market efficiency as there appear to be no exploitable opportunities from predictability and a simultaneous contribution to informational efficiency through the price discovery function.

A key indication of the behavioural traits evident in equity markets is identified in the analysis of the response of relative trading volume to a consecutive series of returns of the same sign. The relationship is consistent across index and equity options whether in aggregate or restricted to out-of-the-money contracts. The evidence presented is consistent with investors' conservative responses to individual pieces of information and updates to beliefs when information follows a quantity of similar information. The updating occurs when the information is perceived to be representative of a trend. The results are a little less clear for out-of-the-money options when open interest is the dependent variable. Behavioural explanations have been offered for the results however the composition of the dataset is likely to be altered following consecutive rises or falls in the underlying asset particularly if there are a large number of options which are fairly close-to-the-money. In interesting extension to this work would be to further segregate the trading volume and open interest data according to moneyness; particularly options that are fairly deep in- or out-of-the-money.

A limitation of this study arises because the Euronext LIFFE database does not sub-divide trading volume by opening or closing of positions or by the category of investor carrying out the transaction. An obvious extension to this work would be to perform analysis of the UK market using data which can be sub-divided in terms of trader sophistication and type of transaction. If trading is correlated with private information then transactions data from the UK options market is likely to provide valuable insights into option trader behaviour and possible predictions for future stock price movements.

Chapter 6

On the Presence of Momentum Effects and Short-Term Overreaction in the UK FTSE100 Index Options Market 2006-2010

6.1 Introduction

The overall objective of this chapter is to test for evidence of momentum effects and short-term overreaction in the UK FTSE100 index options market. More precisely, the relationship between option prices and past market moves and the relationship between option implied volatility and *ex post* realised volatility will be examined. Again the focus will be on the financial crisis period of 2007/8 although momentum and overreaction will also be evaluated across the pre- and post-crisis periods. The first hypothesis is that momentum in stock prices will contribute to investors' expectations about future stock prices. These investor expectations will, in turn, affect the demand for and supply of call and put options. If, as a consequence, the forces of demand and supply induce price pressure then investor expectations about future stock prices provides an additional parameter for the pricing of options. The second hypothesis is that options market investors exhibit short-term overreaction to price changes. However, in common with Gettleman, Julio and Risik (2011) it is hypothesised that overreaction is conditional on significant price changes over a relatively short time period.

Literature which evaluates underreaction and momentum strategies in the context of equity markets is relatively common and has been discussed in Chapter 1, section 1.7.2. Evidence of the relationship between option prices and stock market momentum is relatively sparse in comparison. However Amin, Coval and Seyhun (2004) partially address this apparent gap in the literature and produce evidence to indicate that, where markets are imperfect, past stock returns exert a strong influence on S&P100 option prices.

Evidence of long term overreaction in the options market was first presented by Stein (1989). Poteshman advanced research into this area and produced evidence consistent with long term overreaction and short term underreaction. In contrast to Poteshman, evidence of short term overrreaction conditional on preceding sharp stock price moves was identified by Gettleman, Julio and Risik (2011). Gettleman *et al* then constructed portfolios of stocks and options, on the basis of this overreaction, that were found to produce consistent abnormal profits. All of the above studies focus on the US aggregate or individual stock and options markets.

This chapter contributes to the literature by analysing the UK index options market for both evidence of momentum effects and conditional short term overreaction. If evidence of these effects are found in options markets, these findings will complement similar evidence found in equity markets most notably be DeBondt and Thaler (1985, 1987) and Jegadeesh and Titman (1993). Consistent with chapters 4 and 5, the analysis centres on the time period around the 2007/8 financial crisis.

The motivation to examine for a momentum effect in the UK market is to identify whether a demand-driven parameter is important in the pricing of FTSE100 index options. Tests for momentum effects involve a non-parametric approach of put-call parity violations and a parametric approach of implied volatility spreads. The behaviour of each of these measures is examined in light of previous returns on the underlying market. The financial crisis of 2007/8 should be a particularly interesting time to examine put-call parity violations as it contains a period of restrictions on short selling. Nishiotis and Rompolis (2010) find a significant increase in the magnitude of put-call parity violations during the 2008 short sales ban in the US. They attribute the increase in the size of violations to either overpriced stocks during the ban as a consequence of the limited ability of arbitrageurs to offset the influence of overly optimistic investors on stock prices, or the delay in informational feedback from the options market to the stock market. They also find that put prices become expensive relevant to equivalent calls as they provide an alternative to short selling. Furthermore the magnitude of put-call parity violations are found to be significant predictors of future stock market returns.

The second objective of this chapter is to test for short-term option trader overreaction to sharp declines in stock prices. Anecdotal evidence that investors access the options market to act rapidly on pressing information, as noted in Gettleman *et al*, partly motivates an evaluation of overreaction. Furthermore, evidence of systematic short-term overreaction to declines in stock price may offer opportunities for profitable trading strategies which poses a challenge to the efficient markets hypothesis.

6.2 Data

The data set comprises European style put and call options written on the FTSE100 index. Restricting the sample to the largest and most actively traded segment of the UK traded options market reduces the possibility of any liquidity issues. Options data are purchased from Euronext LIFFE whilst data on interest rates and Futures prices are obtained from Datastream. The option prices are daily closing prices and are calculated as the mid-point of the bid-offer spread. The spot price is that of the FTSE100 index, taken when the options market closes, for the put-call parity tests and the relevant futures price for the implied volatility spreads.

The entire sample period runs from 8th September 2006 to 31st December 2010 although various sub-periods are selected in the analysis. Omissions in the LIFFE database have led to the exclusion of 37 days of observations from the sample.

Options without positive trading volume are also excluded. All but four of these omitted observations are from 2010. The sample contains 18,020 matched pairs of options.[25] Options are 'paired' by either strike price or moneyness depending upon the type of test to be performed. Options need to be paired by strike price for the put-call boundary violation tests and by moneyness for the implied volatility spread.

6.3 Momentum

6.3.1 Methodology

The hypothesis to be tested is that there is a divergence of put and call prices as a function of past stock returns over the period September 2006 through December 2010. An increase in stock prices over a 60-day period will lead to an increase in the price of calls relative to that of puts and a corresponding decrease will lead to an increase in the price of puts relative to that of calls. The 60-day period is consistent with that selected by Amin, Coval and Seyhun (2004) and, although not definitive, is judged a reasonable time frame for momentum tests and is sufficiently distinct from the 5-day event period used in the subsequent overreaction tests. The options data comprises end of day prices, strike prices and maturities for calls and puts. Options are sorted into pairs in terms of moneyness and maturity. For example, for the put-call-parity tests, a nearest to the money series is produced containing put and call options with identical specifications. Four further series are produced: an in (out)-of the money put (call) with the corresponding (out-of) in-the-money call (put). Options further in- or out-of-the-money are not used due to relatively low trading volume and the consequent potential for stale prices. In terms of maturity, the options selected

[25] A small number of pairs were omitted from the implied volatility spreads in cases where the software was unable to solve the option pricing model for volatility. This also serves to exclude all pairs containing options without a positive intrinsic value.

are for the first and second quoted months plus the next traded month on the March, June, September, December cycle which has not already been included in the first two maturity sets. Again, longer maturity options are excluded due to the problem of stale prices. Hence the sample consists of 5 exercise prices and 3 maturity ranges giving a total of 15 series of put-call pairs.

The underlying index value is selected at the time the options market closes. As the options under consideration are the most liquid contracts then, consistent with Gettleman *et al*, the 1 month treasury-bill rate is selected as the riskless rate of interest. The test procedure is based on the assumption that option traders accurately forecast future dividends up to the expiry date of each option. Stock returns are analysed over a 60-day period.

The initial test involves identification of violations of put-call boundary conditions. In particular the following put-call parity relationship will be examined:

$$B = p + Se^{-qT} - c - Ke^{-rT} \tag{6.1}$$

Values of greater than zero indicate that puts are overpriced relative to calls whilst values of less than zero indicate that calls are overpriced relative to puts. Importantly, systematic violations of the boundary conditions as a function of past stock returns provide evidence supportive of the market momentum hypothesis. The probability of boundary violations is given by:

$$Prob = \frac{Total\ number\ of\ observations\ of\ positive\ violation}{Total\ number\ of\ boundary\ condition\ observations} \tag{6.2}$$

The use of end-of-day option prices and closing index prices comes with the caveat that it is not possible to precisely measure deviations from put-call parity as, even in the most liquid of markets, there are non-synchronous trading problems and transactions costs. However, this does not represent a significant problem for the momentum and overreaction tests performed here as the objective is to identify pressures on option prices. In particular, to examine the change in magnitude of the violations following return behaviour of the underlying index.

The second test is a parametric test of the overpricing of calls relative to puts using a volatility spread. It is hypothesised that puts will be overpriced relative to calls following negative 60-day returns and that calls will be overpriced relative to puts following positive 60-day returns. Further, it is hypothesised that the more positive (negative) the 60-day returns, the larger (smaller) will be each implied volatility spread. The implied volatility spread is presented in equation 6.3:

$$IV_{M,T_t} = CIV_{M,T_t} - PIV_{M,T_t} \quad (6.3)$$

Where C and P denote FTSE100 calls and puts and the subscripts indicate the contracts' moneyness and maturity.

The LIFFE database does not contain implied volatilities hence the volatility spread needs to be computed for each of the put-call pairs. The volatility spread is calculated as the implied volatility of a call relative to a put with identical contract specifications and with the same degree of moneyness. The test is model-dependent as an option pricing model is required for the computation of implied volatility. The Black Scholes model, with the futures price used for the underlying asset, is used to calculate implied volatility for all of the index options. Put and call implied volatilities as a function of positive and negative 60-day stock returns are examined separated by exercise price and maturity. The implied volatility spreads are then regressed on past market returns in order to quantify the differential response of put and call implied volatilities to these returns. The regression is given in equation 6.4:

$$\boldsymbol{IVS_{M,T_t} = a + bRFTSE_{t-k,t-1} + e_t} \quad (6.4)$$

Where:

$IVS_{M,T}$ is the implied volatility spread for moneyness M and maturity T

$RFTSE_{t-k,t-1}$ is the return on the FTSE100 index from day t-k to day t-1

6.3.2 Results

6.3.2.1 Put-Call Parity Boundary Violation Tests

The first set of results, presented in Table 6.2, report the mean boundary condition violations and the probability of boundary condition violations ($B > 0$) following past 60-day returns. A negative mean violation indicates that puts are expensive relative to equivalent calls. The results are also partitioned according to moneyness where series 1 contains the furthest out-of (in)-the-money calls (puts), series 3 at-the-money puts and calls and series 5 the furthest out-of(in)-the-money puts (calls). Average moneyness (strike price divided by index) of each series is given in table 6.1.

Table 6.1 Average Moneyness of Series of Option Pairs

	Series of Option Pairs				
	1	2	3	4	5
Moneyness	1.05805	1.02956	0.99995	0.98754	0.97913

Table 6.2 Put Call Parity Boundary Condition Tests Based on Past 60-Day Market Returns

$B = p - c + Se^{-qt} - Ke^{-rt}$

Panel A

Return	**Mean Violation**				
	Moneyness				
	1	**2**	**3**	**4**	**5**
R>0.15	-5.38865	-5.37357	-5.2451	-5.19819	-5.18209
0.15>R>0.1	-3.70799	-3.67564	-3.62176	-3.54701	-3.44933
0.1>R>0.05	-0.75972	-0.72732	-0.70061	-0.64417	-0.57583
0.05>R>0	3.990654	4.020536	4.026766	4.058361	4.113182
0>R>-0.05	1.920414	1.970254	2.000886	1.768342	1.864858
-0.05>R>-0.1	-3.27251	-3.20252	-3.18744	-2.99084	-2.92752
-0.1>R>-0.15	-2.77103	-2.66172	-2.57805	-2.33576	-7.37072
-0.15>R	-3.24004	-3.16986	-3.08217	-1.71789	-3.04679

Panel B

Return	**Probability Violation>0**				
	Moneyness				
	1	**2**	**3**	**4**	**5**
R>0.15	0.190476	0.190476	0.190476	0.190476	0.190476
0.15>R>0.1	0.257862	0.257862	0.264151	0.264151	0.264151
0.1>R>0.05	0.336296	0.334815	0.336296	0.336296	0.334815
0.05>R>0	0.467066	0.469062	0.469062	0.471058	0.467066
0>R>-0.05	0.43609	0.43609	0.438596	0.441103	0.443609
-0.05>R>-0.1	0.264798	0.264798	0.264798	0.264798	0.267913
-0.1>R>-0.15	0.326667	0.326667	0.340000	0.333333	0.313333
-0.15>R	0.296296	0.310185	0.305556	0.351852	0.347222

The mean violations for each set presented in panel A of Table 6.2 are given in index points. The probabilities of boundary condition violations are given in panel B. An observation is not considered a violation if its magnitude is 5 index points or less in order to make some allowance for non-synchronous prices and trading costs.

There is a negative relationship between past index returns and the mean boundary condition violations where past 60-day returns are either greater than 5% or less than 5%. The relationship is increasing in returns where returns are positive indicating the call prices are being bid up relative to puts by an increasing margin. The relationship is robust to the moneyness of each series. Where past index returns are between +5% and -5% the mean boundary violations are positive indicating that in this region puts are overpriced relative to calls. One possible interpretation is that positive or negative past returns of a relatively small magnitude are perceived by investors as a downward trend. However, negative past returns of a relatively large magnitude are perceived as temporary, indicating that investors view the market as mean-reverting.

The probability of a boundary violation, with B > 0, is negatively related to past returns in the range of greater than +15% to +5%. This result is inconsistent with the market momentum hypothesis in that call prices are successively lower relative to those of puts following increases in the value of the index. However, for the range of returns from +5% to -0.15% the relationship is generally positive. This result is consistent with the market momentum hypothesis in that put prices are successively higher relative to those of calls following decreases in the value of the index. The exception is for the range of past returns between -10% and -15% which is associated with more positive violations than the range of past returns between -5% and -10%. Again the relationship is robust to the moneyness of each series. The results are quite similar to those of Amin, Cohal and Seyhun (2004), for the S&P100 market, suggesting that demand may have some role in option pricing across markets and time periods. Amin *et al* interpret their findings as past returns exerting a strong influence on index option prices. Although the results above offer some support for this view it is debatable whether they are strong enough to draw the same conclusion.

As a further robustness check the probability of positive boundary violations conditional on a boundary violation are presented in Table 6.3. As expected this increases the magnitude of the statistics but does not alter the results and their interpretation. What it does indicate is that, according to the put-call parity relationship, FTSE100 index puts are priced high relative to calls following all past 60-day returns other than those between -0.05% and +0.05%.

Table 6.3 Probability of a Put-Call Parity Violation

Return	**Probability Violation>0 Conditional on Probability Violation**				
	Moneyness				
	1	**2**	**3**	**4**	**5**
R>0.15	0.2707	0.222222	0.222222	0.222222	0.222222
0.15>R>0.1	0.350427	0.350427	0.352941	0.358974	0.304348
0.1>R>0.05	0.466119	0.466942	0.468041	0.469979	0.42803
0.05>R>0	0.619048	0.616797	0.619236	0.620237	0.617414
0>R>-0.05	0.535385	0.537037	0.53681	0.536585	0.539634
-0.05>R>-0.1	0.326923	0.324427	0.326923	0.32567	0.311594
-0.1>R>-0.15	0.424242	0.426087	0.437768	0.434783	0.391667
-0.15>R	0.390244	0.403614	0.39521	0.444444	0.438596

6.3.2.2 Parametric Momentum Tests: Implied Volatility Spreads and Past Returns

The parametric approach permits a more general evaluation of the market momentum hypothesis as it is not restricted to boundary violations. It also allows analysis of the relationship between past index returns and the magnitude of violations. Using a range of option moneyness and maturities in the sample helps to address any systematic mispricing issues inherent in the option pricing model.

Table 6.4 contains the implied volatilities of FTSE100 put (Panel A) and call (Panel B) options separated by moneyness and maturity. Panels A and B are sub-divided according to positive 60-day FTSE100 returns (greater than 5%) and negative FTSE100 returns (less than -5%).

Table 6.4 Put and Call Implied Volatilities Based on Past 60-Day Market Returns

Panel A

K*	1	2	3	4	5
Call implied volatility when R > 0.05					
N	0.197438	0.173219	0.173219	0.173066	0.173949
M	0.188042	0.257731	0.179455	0.177204	0.269947
F	0.193502	0.182106	0.179279	0.175032	0.170674
Call implied volatility when R < -0.05					
N	0.307015	0.300577	0.293593	0.288918	0.286878
M	0.333359	0.170911	0.278298	0.288276	0.413432
F	0.390542	0.27722	0.272738	0.266802	0.260377

Panel B

K*	1	2	3	4	5
Put implied volatility when R > 0.05					
N	0.094922	0.17503	0.168238	0.168577	0.166573
M	0.20351	0.282057	0.193182	0.190054	0.311298
F	0.206614	0.226741	0.218973	0.214107	0.210535
Put implied volatility when R < -0.05					
N	0.138017	0.309045	0.304513	0.298316	0.292806
M	0.367267	0.204485	0.307579	0.31615	0.443885
F	0.390631	0.282212	0.323165	0.316223	0.310124

K* is the standardised exercise price which is the exercise price divided by the contemporaneous price of the underlying.

The results presented in table 6.4 are as expected in the sense that all of the implied volatility estimates increase as the FTSE100 index declines. A switch in returns from 5% to -5% increases call implied volatility, on average, by 10.4 percentage points from 19.1% to 29.5%. Similarly for puts, implied volatility increases, on average, by 10.5 percentage points from 20.2% to 30.7%. The results are mostly robust across moneyness and maturity apart from one apparently anomalous middle maturity put-call pair with moneyness category 2. Here the implied volatility changes are reversed giving the appearance of a data error; however, this is not the case. To properly assess the difference between the changes in the respective implied volatilities of put and call options it is necessary to analyse the implied volatility spreads.

Implied volatility spreads need to be generated from put and call options which are matched on moneyness and maturity. Achieving series that are appropriately matched necessitates dropping some observations. Nevertheless the sample size remains large enough (15,470 in total) to be able to draw meaningful conclusions. Two important comparisons are made. First the difference in expensiveness following a negative and a positive price change in the price of the underlying asset over a 5-day period of the same magnitude. Second, the size of the volatility spread following a 10% as opposed to a 20% change in the price of the underlying asset.

6.3.3 Implied Volatility Spread Results

Each series of implied volatility spread is categorised in terms of moneyness; series 1 is the furthest out of the money, series 3 at the money and series 5 furthest in the money. Moneyness for calls is calculated as K/F for calls and the reciprocal for puts. The average moneyness values for each series are presented in table 6.5. N denotes the number of observations for each series.

Table 6.5 Moneyness of Implied Volatility Spreads

Maturity	Near	N	Mid	N	Far	N
1	1.018571	979	1.027191	1053	1.029135	1042
2	1.00917	1031	1.009484	992	1.017396	1059
3	1.000014	1055	1.000081	1042	1.000032	1060
4	0.990942	1031	0.990768	992	0.982982	1060
5	0.981802	980	0.973754	1052	0.971849	1042

Sample statistics for the at-the-money implied volatility spreads are presented in table 6.6. These are broadly representative of the full sample. The sample statistics for the remaining implied volatility spreads are available from the author on request.

Table 6.6 Regression of Implied Volatility Spreads on Past 60-Day Market Returns, September 1 2006 to December 31 2010

	Near	Mid	Far
Mean	-0.010144	-0.025832	-0.048980
Standard Deviation	0.045502	0.025274	0.019646
Maximum	0.196542	0.040256	0.019387
Minimum	-0.136858	-0.136982	-0.128333
ρ_1	0.902	0.865	0.856
ρ_1	0.221	0.292	0.310

The terms ρ_1 and ρ_2 denote partial autocorrelation coefficients.

When daily volatility spreads are used as the dependent variable the residuals exhibit strong autocorrelation however this can be removed in all cases by including 2 lags of the dependent variable in each of the regressions. Each regression is run using the Newey and West (2007) adjustment for autocorrelation and heteroskedasticity. Positive first order partial autocorrelation coefficients of a similar magnitude are interpreted by Amin *et al* (2004) as evidence that the implied volatility spreads follow a slow moving diffusion process. This finding is consistent with changes in the volatility spread being driven by sustained price pressure on options.

Table 6.7 Regression of Implied Volatility Spreads on Past 60-Day Market Returns, September 1 2006 to December 31 2010

$$IVS_{M,T_t} = a + bRFTSE_{t-k,t-1} + e_t$$

Maturity	**Near**	**R^2**	**Mid**	**R^2**	**Far**	**R^2**
Moneyness						
1	-0.531511*** (0.0040)	0.1001	0.163853 (0.1499)	0.0296	0.504818*** (0.0002)	0.2230
2	0.065347** (0.0184)	0.0259	-0.916362*** (0.0000)	0.2603	-0.193741*** (0.0000)	0.1587
3	0.059824* (0.0579)	0.0149	0.049701*** (0.0056)	0.0322	0.044753*** (0.0007)	0.0464
4	0.033266 (0.3793)	0.0023	0.0964328*** (0.0000)	0.2574	0.043862*** (0.0006)	0.0481
5	0.001953 (0.9669)	-0.0010	-0.120298 (0.2507)	0.0179	-0.560827*** (0.0000)	0.2287

Figures in parentheses are p values. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

A number of the coefficients on the 60-day past returns are found to be significant with a mixture of positive and negative signs, however those with negative signs provide the strongest results. In particular, near to maturity moneyness 1, mid to maturity moneyness 2 and far to maturity moneyness 2 and 5 are suggestive of a significant negative relationship between past 60-day FTSE100 returns and the implied volatility spread. This result is consistent with the market momentum hypothesis as past market declines are related to increases in the implied volatility of puts relative to that of calls with matching maturity and moneyness.

6.3.3.1 Sub-Periods

Table 6.8 Regression of Implied Volatility Spreads on Past 60-Day Market Returns, Pre-Crisis; 1st January 2007- 31st May 2007

Maturity	Near	R^2	Mid	R^2	Far	R^2
Moneyness						
1	-0.005214 (0.9597)	-0.0104	1.006374*** (0.0002)	0.1643	0.252575*** (0.0006)	0.2186
2	-0.127237 (0.2802)	0.0114	-0.260631 (0.2532)	-0.0011	-0.006310 (0.8973)	-0.0095
3	-0.253757** (0.0493)	0.0524	0.142778 (0.1352)	0.0471	-0.064221 (0.2693)	0.0196
4	-0.422728*** (0.0041)	0.0935	0.323148 (0.3076)	0.0010	-0.045419 (0.3560)	0.0120
5	-0.679894*** (0.0007)	0.1337	-0.463425** (0.0294)	0.0680	-0.171292 (0.3073)	0.0192

Figures in parentheses are p values. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

The results presented in Table 6.8 indicate that, for the pre-crisis sub-period, nearest to maturity options have negative coefficients although only those with moneyness 3, 4 and 5 are significant. Nevertheless this is an interesting result as these categories contain at-the-money as well as in-the-money puts rather than out-of-the-money options which have been highlighted in the literature reviewed in previous chapters as having the greatest information content. The results for volatility spreads constructed using out-of-the-money options which produce significant coefficients on past returns show a positive relationship. In aggregate the results for the pre-crises period are inconclusive with respect to the market momentum hypothesis.

Table 6.9 Regression of Implied Volatility Spreads on Past 60-Day Market Returns, Crisis June 2007-Dec 2008

Maturity	Near	R^2	Mid	R^2	Far	R^2
1	-1.459756*** (0.0000)	0.5456	0.31933* (0.0886)	0.0648	0.767982*** (0.0006)	0.2335
2	-0.037510 (0.1628)	0.0164	-1.113306*** (0.0000)	0.4279	-0.349771*** (0.0000)	0.2729
3	-0.078573*** (0.0040)	0.065071	-0.046951** (0.0343)	0.0434	-0.018352 (0.1639)	0.0106
4	-0.129994*** (0.0000)	0.1269	1.046768*** (0.0000)	0.3488	-0.014929 (0.2393)	0.0063
5	-0.195703*** (0.0000)	0.1534	-0.282442* (0.0959)	0.0616	-1.005456*** (0.0000)	0.3243

Figures in parentheses are p values. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

The results for the crisis period, presented in Table 6.9, are quite striking in that 9 of the coefficients attached to past FTSE100 returns are negative and significant. This relationship is robust across maturities and moneyness. The implied volatility of puts relative to calls in this sub-period provides the strongest support so far to the market momentum hypothesis.

Table 6.10 Regression of Implied Volatility Spreads on Past 60-Day Market Returns, Post-Crisis Jan 2009 – Dec 2010

Maturity	Near	R^2	Mid	R^2	Far	R^2
1	-0.115984 (0.5601)	0.0031	-0.09816 (0.1116)	0.0184	0.040837 (0.1140)	0.0262
2	-0.060910 (0.1876)	0.0222	-0.493022*** (0.0007)	0.0562	-0.083179** (0.0165)	0.0484
3	-0.073923 (0.1644)	0.0218	-0.007316 (0.6827)	-0.0008	0.019945 (0.4138)	0.0082
4	-0.113305* (0.0771)	0.0332	0.480255*** (0.0009)	0.0507	0.019098 (0.4351)	0.0074
5	-0.165477** (0.0313)	0.0451	0.108751 (0.1606)	0.0167	-0.040949** (0.0563)	0.0223

Figures in parentheses are p values. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

The results presented in Table 6.10, relating to the post-crisis sub-period are much less conclusive than those in the previous sub-period. However, out of the 7 significant coefficients attached to past FTSE100 returns 6 are found to be negative. The results are fairly evenly dispersed across maturity and moneyness and provide some support, albeit weaker than from the previous sub-period, for the market momentum hypothesis.

Overall the tests performed by regression 60-day past FTSE100 returns on implied volatility spreads generated using FTSE100 options provide considerable support for the market momentum hypothesis. It seems that demand does have a role to play in the pricing of options.

6.4 Short-Run Overreaction

6.4.1 Introduction

This section further examines the relationship between past FTSE100 returns and FTSE100 index option prices, under the assumption that demand is instrumental in option pricing. In order to examine for overreaction, market price changes are selected which are the most extreme in the sample and are over much shorter time periods than the 60-day period analysed in the previous section. The objective is to evaluate whether options investors exhibit short-term overreaction following sharp movements in the FTSE100. It seems quite reasonable that option traders will be much more inclined to write options conditional on recent stock price changes than to write these unconditionally. The hypothesis is therefore that puts will become overpriced following steep declines in the index and that, the more pronounced the decline, the greater the overpricing. The same data set as used in the momentum analysis is used for the overreaction tests. However, the testing procedure is somewhat different and focuses on a measure of expensiveness. The measure of expensiveness is given by the difference between implied volatility and *ex post* realised volatility for the remaining life of the option. If implied volatility is significantly and consistently different to *ex post* realised volatility this implies that options are mispriced. For the purposes of this study the focus will be on whether implied volatility exceeds *ex post* realised volatility both unconditionally and conditional on sharp, short-term price changes in the underlying asset. Conditional excess volatility relative to *ex post* realised volatility is employed by Gettleman, Julio and Risik (2011) as a measure of expensiveness. If options are found to be consistently ‘expensive’ following sharp, short-term changes in the value of the underlying asset then this is interpreted as option traders overreacting to information. In this respect they perceive a short sequence of price changes leading to a significant rise or fall in the underlying asset as indicative of a trend.

The overreaction tests are performed in event time. Hence the options that are included in the tests are selected conditional on recent underlying index returns. The definition of an event relating to a broad market index is somewhat arbitrary. To address this, 5-day return groups are sorted according to their magnitudes. The sample is divided into deciles and ranked lowest to highest. Deciles 1, 2, 9 and 10 are analysed and are defined as follows:

Decile 1 – the most negative five day returns in the sample

Decile 2 – the second most negative five day returns in the sample

Decile 9 – the most positive five day returns in the sample

Decile 10 – the second most positive five day returns in the sample

After sorting a number of observations are removed from each of the examined deciles to ensure no overlapping of events. The event windows are non-overlapping in the sense that if an event occurs in a particular 5-day period, no subsequent event period can begin until that 5-day period is complete.

Five categories of options are considered with category 1 being furthest in-the-money, category 2 in-the-money, category 3 at- or close to-the-money, category 4 out-of-the-money and category 5 furthest out-of-the-money. This means that the sample contains pairs of options with a variety of strike prices but maintains a consistent relationship with the value of the underlying index throughout the entire period. The measure of expensiveness is compared across each category with a common maturity date. Only the most liquid options are included in the sample to ensure the reliability of prices. The maturity of the options selected is a maximum of six months with no options included with less than one week to expiration. *Ex post* realised volatility is calculated as the volatility of the underlying asset over the remaining life of the option subsequent to an extreme market movement. It is computed as follows:

$$RV = \sum_{t=1}^{N} \sqrt{\frac{252}{N} r_t^2} \qquad (6.3)$$

Where r_t is the daily return on the underlying asset

The analysis is performed using averages of implied volatility and expensiveness for each maturity and moneyness combination. Expensiveness is defined as the difference between implied volatility and the *ex post* realised volatility of the underlying asset up to the maturity of the option under consideration. Tables 6.11 and 6.12 contain unconditional implied volatilities and measures of expensiveness for each moneyness and maturity taken over the entire sample period. Tables 6.13

to 6.16 contain implied volatilities and moneyness measures conditional on past 5-day returns.

Table 6.11 Unconditional Implied Volatilities

Moneyness	1	2	3	4	5
Panel A: Calls					
Near	0.199616	0.199687	0.201523	0.208891	0.21877
Mid	0.305517	0.199778	0.199956	0.210888	0.296687
Far	0.189493	0.193956	0.198259	0.20112	0.241676
Average	0.231542	0.197807	0.199913	0.206966	0.252378
Panel B: Puts					
Near	0.135532	0.217051	0.211578	0.209584	0.207989
Mid	0.317583	0.237265	0.225812	0.224878	0.341323
Far	0.2593	0.23946	0.247285	0.241923	0.238064
Average	0.237472	0.231259	0.228225	0.225462	0.262459

In most cases put implied volatilities exceed those of the corresponding calls. This relationship is most pronounced, on average, for at-the-money and closest in-the-money options. There is also clear evidence of a skewed volatility smile with the smile for puts sitting above that for calls apart from one low paired observation for nearest to maturity, deepest-in-the-money options.

The unconditional expensiveness indicates the magnitude of implied volatility relative to *ex post* realised volatility up to the maturity of the option. A positive figure indicates that the implied volatility exceeds the *ex post* realised volatility. It follows that a positive figure identifies an option as being overpriced according to its implied volatility.

Table 6.12 Unconditional Expensiveness

Moneyness	1	2	3	4	5
Panel A: Calls					
Near	-0.01727	-0.0155	-0.01212	-0.0052	0.004057
	(-0.00485)	(-0.00467)	(-0.0036)	(-0.00152)	(0.001146)
Mid	0.089531	-0.01005	-0.01299	-0.00539	0.058836
	(0.024115)	(-0.00301)	(-0.00405)	(-0.00153)	(0.014672)
Far	-0.03159	-0.02713	-0.02283	-0.02001	0.020168
	(-0.00939)	(-0.00798)	(-0.00663)	(-0.0057)	(0.004634)
Average	0.013557	-0.01756	-0.01598	-0.0102	0.027687
Panel B: Puts					
Near	-0.07918	0.002962	-0.00207	-0.0056	-0.0089
	(-0.01328)	(0.000964)	(-0.00068)	(-0.00184)	(-0.00264)
Mid	0.079732	0.020986	0.012867	0.015048	0.125337
	(0.020584)	(0.006334)	(0.004373)	(0.004765)	(0.031218)
Far	0.037792	0.01833	0.0262	0.020838	0.016979
	(0.009404)	(0.005343)	(0.008019)	(0.006408)	(0.005258)
Average	0.012781	0.014093	0.012332	0.010095	0.044472

Figures in parentheses are t-statistics.[26]

The values in Table 6.12 are consistent with puts, on average, being unconditionally more expensive than respective calls for all moneyness other than furthest out-of-the money. However none of the expensiveness figures presented here are statistically significant so meaningful inferences on their size and/or their magnitude cannot be drawn.

[26] Critical values are not presented as the partitioning of the data results in a wide range of sample sizes.

Table 6.13 Expensiveness Decile 1

Moneyness	1	2	3	4	5
Panel A: Calls					
Near	-0.07931***	-0.03148	-0.03076**	0.007087	-0.01213
	(-3.29267)	(-0.03148)	(-1.80373)	(0.55469)	(-0.8788)
Mid	0.05627**	-0.01459	-0.02414*	-0.0108	-0.00149
	(2.174889)	(-0.81267)	(-1.53437)	(-0.76208)	(-0.08568)
Far	-0.02377*	-0.02126*	-0.01371	-0.01252	0.014599
	(-1.67188)	(-1.49585)	(-0.99462)	(-0.90552)	(0.771987)
Average	-0.0156	-0.02244	-0.02287	-0.00541	0.000326
Panel B: Puts					
Near	0.020932**	0.004952	-0.02556**	-0.02735	-0.07284***
	(-2.13358)	(0.422983)	(-1.69192)	(-0.02735)	(-3.38366)
Mid	0.01182	-0.002	-0.01105	-0.00181	0.093884***
	(0.686513)	(-0.15515)	(-0.76856)	(-0.10495)	(3.42346)
Far	0.020932	-0.00887	0.003545	0.000135	-0.00186
	(1.106648)	(-0.66855)	(0.268569)	(0.009787)	(-0.13794)
Average	-0.00891	-0.00197	-0.01102	-0.00968	0.006395

Figures in parentheses are t-statistics. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Following the largest 5-day negative returns, of the nine coefficients that are statistically significant only two are positive. This indicates that option implied volatility is lower than *ex post* realised volatility in the overwhelming majority of moneyness/maturity combinations. This result does not support the hypothesis that FTSE100 option investors exhibit short-run overreaction by bidding up put option prices in response to sharp negative market returns. However, it does indicate that call option prices are bid down following sharp negative market returns, particularly for call options closest to the money.

Table 6.14 Expensiveness Decile 2

Moneyness	1	2	3	4	5
Panel A: Calls					
Near	-0.00452	-0.0127	-0.00729	-0.00042	0.006468
	(-0.24433)	(0.086164)	(-0.71906)	(-0.03896)	(0.560752)
Mid	0.112957***	-0.00827	-0.0049	-0.00093	0.012188
	(8.249059)	(-0.81095)	(-0.4868)	(-0.08614)	(0.995813)
Far	-0.0206**	-0.01293*	-0.00987	-0.00741	0.020506*
	(-1.89259)	(-1.31679)	(-0.92103)	(-0.68296)	(1.512978)
Average	0.029279	-0.0113	-0.00735	-0.00292	0.013054
Panel B: Puts					
Near	-0.05208***	0.000438	-0.00215	-0.00856	-0.00704
	(-2.89599)	(0.046667)	(-0.24258)	(0.077798)	(-0.38386)
Mid	0.030055***	0.014172*	0.011793	0.007365	0.152831***
	(2.419228)	(1.425092)	(1.26491)	(0.788595)	(10.15199)
Far	0.031364***	0.017856*	0.02239**	0.020666**	0.01436*
	(2.463996)	(1.633728)	(2.155559)	(2.201791)	(1.38588)
Average	0.003113	0.010822	0.010678	0.00649	0.053384

Figures in parentheses are t-statistics. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

In contrast to those in table 6.13, the results in table 6.14 are consistent with short-term overreaction to negative price changes of a smaller magnitude. In almost all cases, where implied volatility is significantly different to *ex post* realised volatility, puts exhibit positive expensiveness. The results on calls are inconclusive given the even split between positive and negative significant values. The results so far indicate that options investors are more inclined to bid up put option prices in response to negative 5-day returns when the magnitude of the change is smaller rather than larger.

Table 6.15 Expensiveness Decile 10

Moneyness	1	2	3	4	5
Panel A: Calls					
Near	-0.01024*	-0.00382	-0.00248	0.002781	0.007009
	(-1.59155)	(0.086771)	(-1.10017)	(-0.48858)	(0.047069)
Mid	0.105102***	0.004957*	-0.00675	0.001267	0.017353
	(5.790247)	(-1.38289)	(-1.18441)	(-0.92569)	(-0.49533)
Far	-0.0111**	-0.00748**	-0.00635*	-0.00443*	0.03014
	(-2.17143)	(-1.94877)	(-1.41587)	(-1.37167)	(0.265096)
Average	0.027921	-0.00211	-0.00519	-0.00013	0.018167
Panel B: Puts					
Near	-0.04896***	0.003692	-0.00126	-0.0028	-0.00625
	(-2.5646)	(-0.01203)	(-0.59484)	(0.0781)	(-1.23719)
Mid	0.030697	0.011673	0.003722	0.015557	0.143081***
	(1.021417)	(0.455377)	(0.243694)	(0.039902)	(7.341759)
Far	0.0337	0.008939	0.014286	0.016497	0.013436
	(1.218581)	(0.735573)	(1.175691)	(0.822241)	(0.48241)
Average	0.005146	0.008101	0.005583	0.009751	0.050089

Figures in parentheses are t-statistics. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

The results presented in table 6.15 do not provide support for the short-term overreaction hypothesis. Expensiveness values for puts are only significant in two instances, one positive and one negative, so no inferences can be drawn. Furthermore, call implied volatility is not found to be consistently higher than *ex post* realised volatility following the largest positive past 5-day returns on the FTSE100 index. Only mid to maturity in-the-money calls produce expensiveness values that are positive and significant.

Table 6.16 Expensiveness Decile 9

Moneyness	1	2	3	4	5
		Panel A: Calls			
Near	-0.02067	-0.01309	-0.01169	-0.00529	0.007009
	(-0.72343)	(0.072143)	(-0.25041)	(0.264111)	(0.641075)
Mid	0.084645***	-0.01622	-0.01323	-0.01051	-0.00641
	(6.371722)	(0.338969)	(-0.59671)	(0.099915)	(1.126765)
Far	-0.02421	-0.02161	-0.01538	-0.0162	0.002586**
	(-0.99423)	(-0.66902)	(-0.52555)	(-0.36272)	(1.742325)
Average	0.013255	-0.01697	-0.01343	-0.01067	0.001062
		Panel B: Puts			
Near	-0.04896**	-0.00011	-0.00564	-0.00667	-0.0153
	(-2.29877)	(0.397759)	(-0.14295)	(0.064815)	(-0.50201)
Mid	0.012805**	0.004741	0.0025	0.000442	0.115954***
	(1.997335)	(0.95941)	(0.363331)	(1.095013)	(8.051304)
Far	0.011813	0.008259	0.012016	0.008613*	0.005062
	(0.004503)	(0.738945)	(1.210976)	(1.509802)	(1.239264)
Average	-0.00811	0.004297	0.002959	0.000795	0.035239

Figures in parentheses are t-statistics. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

The results in table 6.16 are largely consistent with those in table 6.15 providing little support for the short-term overreaction hypothesis. Although all of the significant expensiveness values for calls have the expected sign, this only applies to two observations. Three out of four significant put values have positive signs indicating that investors appear more likely to bid up index put option prices following the second-largest category of positive index returns. However, the large number of insignificant values provides little support for the overreaction hypothesis.

In aggregate the results can, at best, be regarded as providing very weak support for the overreaction hypothesis. This finding is in contrast to, but does not contradict, that of Gettleman, Julio and Risik (2011) as they focus on the market for individual equity options rather than index options.

The characteristics of the sample period, particularly the volatility of the market, may go some way towards explaining the seemingly counter-intuitive results. One possible explanation for the lack of positive and significant expensiveness figures for put options when 5-day returns are most negative is the extremely high market volatility in the second half of 2008.[27] In order to test this explanation the data is partitioned according to the pre-crisis, crisis and post-crisis periods defined earlier. Unconditional implied volatility and unconditional expensiveness can then be examined across each sub-period. It is not worthwhile further partitioning these sub-periods due to the clustering of negative and positive returns. Results are presented in tables 6.17 to 6.22.

Table 6.17 Unconditional Implied Volatilities Pre-Crisis Period

Moneyness	1	2	3	4	5
Panel A: Calls					
Near	0.096883	0.090779	0.09033	0.092723	0.096572
Mid	0.15997	0.096323	0.097942	0.09803	0.097191
Far	0.094152	0.095084	0.094882	0.09166	0.095665
Average	0.117002	0.094062	0.094385	0.094138	0.096476
Panel B: Puts					
Near	0.137843	0.130535	0.126482	0.128491	0.138379
Mid	0.148708	0.141539	0.140015	0.138601	0.190454
Far	0.152025	0.16066	0.156514	0.154282	0.154631
Average	0.146192	0.144245	0.141004	0.140458	0.161155

Table 6.17 indicates that implied volatilities of index puts exceed those of corresponding index calls across the moneyness range for the pre-crisis period. There is evidence of a negatively skewed volatility smile for puts although this is less pronounced than that for the entire period.

[27] For example UK market volatility in excess of 50% was regularly observed during the final third of 2008.

Table 6.18 Unconditional Expensiveness Pre-Crisis Period

Moneyness	1	2	3	4	5
Panel A: Calls					
Near	-0.0046	-0.01034	-0.01067	-0.0085	-0.00626
	(-0.00922)	(-0.02224)	(-0.0221(	(-0.01759)	(-0.01252)
Mid	0.053284	-0.01043	-0.00874	-0.00821	-0.0095
	(0.077795)	(-0.03049)	(-0.02516)	(-0.02387)	(-0.02564)
Far	-0.04186	-0.04093	-0.04113	-0.04435	-0.04084
	(-0.06527)	(-0.08209)	(-0.08196)	(-0.08765)	(-0.07325)
Average	0.002275	-0.02057	-0.02018	-0.02035	-0.01887
Panel B: Puts					
Near	0.03501	0.029308	0.02548	0.027367	0.036898
	(0.073343)	(0.059567)	(0.04923)	(0.053251)	(0.064345)
Mid	0.042022	0.035304	0.033329	0.031847	0.083768
	(0.113442)	(0.097324)	(0.090835)	(0.089114)	(0.15937)
Far	0.015518	0.02465	0.020501	0.018269	0.018618
	(0.028365)	(0.050095)	(0.041623)	(0.037312)	(0.144804)
Average	0.03085	0.029754	0.026437	0.025828	0.046428

Figures in parentheses are t-statistics.

None of the values presented in table 6.18 are statistically significant. This means that neither calls nor puts are overpriced according to the measure of expensiveness. The clear inference is that implied volatility is not significantly different to *ex post* realised volatility in the pre-crisis period.

Table 6.19 Unconditional Implied Volatilities Crisis Period

Moneyness	1	2	3	4	5
Panel A: Calls					
Near	0.220463	0.222243	0.223989	0.229999	0.234711
Mid	0.349064	0.22643	0.220124	0.240304	0.262316
Far	0.209368	0.213744	0.217868	0.22132	0.312064
Average	0.259632	0.220806	0.22066	0.230541	0.269697
Panel B: Puts					
Near	0.173735	0.265647	0.2623	0.260673	0.253102
Mid	0.310175	0.283444	0.262393	0.26831	0.371556
Far	0.326869	0.25251	0.277477	0.271729	0.267356
Average	0.27026	0.2672	0.26739	0.266904	0.297338

Table 6.19 indicates that put implied volatility continues to exceed that of calls although by a smaller amount. Furthermore, the volatility smile is much more pronounced than in the previous sub-period and is clearly evolving over time.

Table 6.20 Unconditional Expensiveness Crisis Period

Moneyness	1	2	3	4	5
Panel A: Calls					
Near	-0.07402	-0.0733	-0.07093	-0.06571	-0.06061
	(-0.02615)	(-0.02836)	(-0.02732)	(-0.0252)	(-0.02303)
Mid	0.050915	-0.06231	-0.07285	-0.05774	-0.03648
	(0.01701)	(-0.02155)	(-0.02811)	(-0.01895)	(-0.00996)
Far	-0.0995	-0.09512	-0.091	-0.08754	0.000809
	(-0.03949)	(-0.03747)	(-0.03555)	(-0.03345)	(0.000203)
Average	-0.04087	-0.07691	-0.07826	-0.07033	-0.03209
Panel B: Puts					
Near	-0.12159	-0.03006	-0.03262	-0.03487	-0.04138
	(-0.02473)	(-0.0117)	(-0.0128)	(-0.0137)	(-0.01475)
Mid	0.011379	-0.0146	-0.03058	-0.02043	0.073407
	(0.003094)	(-0.00485)	(-0.01212)	(-0.00715)	(0.023846)
Far	0.015613	-0.05636	-0.03139	-0.03714	-0.04151
	(0.004171)	(-0.02241)	(-0.01212)	(-0.01439)	(-0.01619)
Average	-0.03153	-0.03367	-0.03153	-0.03081	-0.00316

Figures in parentheses are t-statistics.

On initial inspection, the results presented in table 6.20 indicate that, for all five moneyness categories, implied volatility is less than *ex post* realised volatility during the main crisis period. This period contains data from 2008 when the volatility of the FTSE100 was at its peak. However none of the expensiveness values are statistically significant. This is unsurprising given the evolution in the volatility smile identified in Table 6.19. This set of results offers a plausible explanation for the seemingly counter-intuitive expensiveness statistics presented in table 6.13.

Table 6.21 Unconditional Implied Volatilities Post-Crisis Period

Moneyness	1	2	3	4	5
Panel A: Calls					
Near	0.221784	0.223443	0.225569	0.234878	0.247881
Mid	0.32458	0.218359	0.222958	0.228362	0.234658
Far	0.209371	0.215278	0.221484	0.22624	0.23794
Average	0.251912	0.219027	0.223337	0.229827	0.24016
Panel B: Puts					
Near	0.102908	0.208356	0.201058	0.196789	0.194101
Mid	0.240805	0.233874	0.228856	0.224001	0.373892
Far	0.243277	0.25884	0.256501	0.250258	0.245208
Average	0.195663	0.23369	0.228805	0.223683	0.271067

During the post-crisis period there is little discernible difference between implied volatilities of puts and calls nearest to the money. However there is a clear volatility skew for put options with deepest out-of-the-money volatility approximately 7.5 percentage points higher than deepest in-the-money volatility.

Table 6.22 Unconditional Expensiveness Post-Crisis Period

Moneyness	1	2	3	4	5
Panel A: Calls					
Near	0.030538	0.033803	0.038038	0.047681	0.061503
	(0.01208)	(0.025976)	(0.028472)	(0.034573)	(0.041684)
Mid	0.136778	0.03044	0.035091	0.040589	0.046796
	(0.058046)	(0.031363)	(0.035849)	(0.040943)	(0.047196)
Far	0.030887	0.036795	0.043	0.04776	0.059457
	(0.030787)	(0.036166)	(0.041643)	(0.045445)	(0.052195)
Average	0.066068	0.033679	0.03871	0.045343	0.055919
Panel B: Puts					
Near	-0.08347	0.02116	0.013527	0.007149	0.002855
	(-0.02888)	(0.015469)	(0.009958)	(0.005206)	(0.001222)
Mid	0.052943	0.0461	0.040989	0.036082	0.18609
	(0.054133)	(0.046765)	(0.041456)	(0.031363)	(0.068986)
Far	0.064793	0.08036	0.078018	0.071775	0.066724
	(0.058765)	(0.075118)	(0.0736)	(0.06842)	(0.064304)
Average	0.011422	0.049207	0.044178	0.038335	0.085223

Figures in parentheses are t-statistics.

The results presented in table 6.22 indicate that in the post-crisis period option implied volatilities are not significantly different to *ex post* realised volatilities. It should also be highlighted that the post-crisis period contains the first quarter of 2009 during which high market volatility persisted. Option prices appear to be priced highly yet consistently with the high volatility that was a feature of this period.

It is clear from the preceding analysis that there is no evidence of unconditional overreaction of FTSE100 traders to FTSE100 returns. The evolution of the volatility smile indicates that, unconditionally, option traders price options broadly in line with *ex post* realised volatility.

6.5 Discussion and Conclusion

This chapter has provided an analysis of momentum and short-term overreaction effects in the FTSE100 index options market around the time of the 2007/8 financial crisis.

Model-independent tests for violations of the put-call boundary condition for European-style FTSE100 options following 60-day market returns along with parametric tests of implied volatility spreads are carried out. The results of the put-call boundary violation tests provide some support for the market momentum hypothesis although this is fairly weak. Stronger support is provided by the results of regressions of the implied volatility spread on 60-day FTSE100 returns. These results are interpreted as indicating a role for a demand parameter in option pricing.

The difference between implied volatility and realised volatility of the FTSE100, conditional on significant index price moves, is examined as a measure of expensiveness. These price movements are sorted into deciles with the two most negative and two most positive selected as containing events. Fairly weak evidence of conditional short-term overreaction is found, although in no way can this be interpreted as consistent. This relationship is strongest following the second most negative 5-day price movements (decile 2).

There is no evidence of unconditional overreaction because no significant divergence between implied volatility and *ex post* realised volatility is identified. This result is holds for the entire sample period as well as the pre-crisis, crisis and post-crisis sub-periods. It does not seem that options market investors overreact unconditionally to information at an aggregate level. One possible future extension to this work would be to examine for short-term conditional overreaction using individual equity options traded on Euronext LIFFE.

The volatility smile for options evolves in line with the volatility of the underlying market and is consistent with a negatively skewed risk-neutral distribution. Furthermore put options have consistently higher implied volatilities than call options matched by moneyness and maturity.

Overall, the findings of this chapter support those of Amin, Coval and Seyhun (2004) in inferring a role for demand in option pricing. However, little support is offered for the findings of Gettleman, Julio and Risik (2011). As a consequence, this chapter provides no motivation to construct a portfolio of FTSE100 options and underlying stocks to test whether it is possible to generate systematic profits. If no evidence can be found of short term overreaction it is not possible to form contrarian portfolios.

Chapter 7

Summary, Conclusions and Suggestions for Future Research

7.1 Summary of Issues and Key Contributions

A substantial body of literature has been published that runs counter to the neoclassical paradigm and, in particular rejects the conclusion of an efficient capital market. Furthermore literature has been published which produces evidence in derivative markets which supports the findings in the equity market. In aggregate this literature provides the basis of the behavioural finance paradigm. To address all of the contributions would take several volumes. However, key contributions and subject areas have been covered in this thesis.

A debate between the proponents of efficient markets and those of behavioural finance has continued for over 25 years with little agreement. The debate which was initially focused on the equity market has more recently been extended to the options market and focuses on the key areas of relative pricing, implied volatility and trading behaviour. To date the overwhelming majority of published work has focused on the United States market with data normally sourced from the Chicago Board Options Exchange. The four empirical chapters in this thesis comprise the key areas of options market research with data sourced from Euronext LIFFE for options traded in London. Furthermore the analysis in each chapter is applied to one of the most turbulent decades in financial history encompassing the inflation and subsequent bursting of the dotcom bubble and the liquidity and banking crisis precipitated by the sub-prime lending debacle. The combination of a UK-based study and application to major financial crises makes this work an important contribution to the behavioural finance literature. There is apparently little or no existing literature with this particular focus.

Options provide a means by which to hedge against or speculate on future moves in the price of the corresponding underlying assets. Option writers need some objective parameters by which to price options based on the probability that they will encounter a negative cash flow on exercise/expiry and, if a negative cash flow is encountered, the magnitude of the flow. Academic research has produced a number of models to calculate a fair option price based on observable parameters. Notable models are those of Black, Scholes and Merton (1973) and Cox, Ross and Rubinstein (1979). Attempts have been made to build on this work including prominent models which are able to incorporate stochastic volatility such as those of Hull and White (1987) and Heston (1993). However, the degree of pricing accuracy has not improved greatly despite the proliferation of stochastic volatility models. The one parameter in option pricing models which must be computed is volatility. Volatility has proved to be so problematic that option traders regularly use implied volatility of short-dated at-the-money options to price in- or out-of-the-money and longer-dated options on the assumption that the market price is correct. However this technique is still model-dependent. One key aspect of option pricing is the notion of the option as a redundant asset with cash flows that can be replicated by a combination of risky assets. Hence risk preferences are not included in the models and options are priced under the assumption of risk-neutrality and frictionless markets. If the sentiment of investors is a partial determinant of option price then it will be apparent directly in the relative pricing of puts and calls or indirectly in model-dependent implied volatility. It follows that an opportunity to test this proposition arises in periods of significant market upheaval by examining the relative prices of put and call options with strike prices symmetrically distributed around the price of the underlying asset.

The first empirical chapter in this thesis extended existing research by examining relative put and call prices in the UK index options market over the dotcom bubble period at the turn of the century. The key finding presented in this chapter is that relative option prices and associated implied volatility incorporated the negative expectations of investors at the time of the dotcom bubble. However, this relationship was found to persist during periods of relative tranquillity in markets, supporting the assertion of Rubinstein (1994) that investors suffer from ‘crashophobia’. The calculation of a volatility spread and plotting of the behaviour of the volatility smile across the sample period provided insights into investor behaviour and illustrated the difficulties that option prices with lognormal risk-neutral distributions encounter in pricing index options.

One of the most basic human emotions is fear. The great fear of stock market investors or portfolio managers is that they may lose a substantial amount of the value of their portfolios. Whaley (2000) proposes that this fear in the US is captured by the VIX; an index of implied volatility constructed using options traded on the S&P 500 stock index. Numerous studies have analysed the VIX as a market consensus view of future volatility whilst some have examined it as a predictor of stock market returns. The literature reveals a significant role in volatility forecasting but is much less clear on return predictability. Again, the bulk of the literature is focused on volatility indexes in the US. The UK presents a gap in the literature as the corresponding volatility index constructed from FTSE100 index options, the VFTSE, was introduced fairly recently. This study provides a unique contribution to the literature as a volatility index is constructed which permits analysis of the UK fear gauge prior to the 2008 introduction of the VFTSE. In Chapter 4, the second empirical chapter, a volatility index is constructed, the VUK, using FTSE100 option implied volatilities from 2006 to 2010. A range of tests is applied to establish the relationship between the VUK and the underlying large capitalisation market. Clear evidence is produced to support the notion of the VUK as an index that reflects the fear of UK investors. Furthermore, the VUK is found to be a good, although biased, predictor of the future volatility of FTSE100 returns. No clear evidence of FTSE100 return predictability is found using the VUK indicating that the index is unable to provide any indication of exploitable trading opportunities, at least when daily prices are observed. Hence analysis of the VUK does not produce any evidence that contradicts the efficient markets hypothesis. This represents an important finding because no support for the behavioural finance paradigm is found using UK data in this respect. The behaviour of the VUK is found to be fairly consistent across the financial crisis. The clear negative correlation with index returns supports the notion of the VUK as a fear index. Finally the VUK is found to be mean-reverting.

The third empirical chapter focuses on the third key behavioural issue in options markets; trading behaviour. A number of studies find that patterns of trading behaviour provide insights into investor sentiment. A prominent and thorough example is that of Lakonishok, Lee and Poteshman (2003). A frequent observation is that increases in trading volume and open interest are related to negative spot market returns. Again the overwhelming majority of published literature is focused on US markets. The important contribution to the literature provided by this study is an analysis of the relationship between trading volume/open interest and the UK stock market during the recent financial crisis. The empirical chapter first examines the FTSE100 index and index options but then extends the analysis to a portfolio of financial stocks that have exchange-traded options written on them. This disaggregation is motivated by an expectation that the impact of the financial crisis is likely to be greater than that on the aggregate market. Option portfolios are further disaggregated by constraining the sample to include only out-of-the-money options. The findings of Chapter 4 are supported in that little evidence of return predictability is found. Again, this is an important finding which adds further weight to the case for market efficiency. Some evidence is presented to support the price discovery role of trading volume. Taken together these findings are consistent with the efficient markets hypothesis. The most important finding in this chapter regards the change in investor behaviour in response to a series of return innovations of the same sign as opposed to a single return innovation. The put/call ratios of trading volume and of open interest are shown to be negatively and significantly related to contemporaneous spot market returns when there are three or more return innovations of the same sign. However, no significant relationship is found between the put/call ratios and daily innovations. This finding provides a clear indication that UK investors are subject to conservatism and the representative heuristic. It seems that the behavioural biases commonly observed in the equity market are also present in the options market.

The fourth empirical chapter examines for evidence of momentum effects and overreaction in the UK index options market over the financial crisis period of 2007/8. Both a non-parametric approach and a parametric approach are employed to test for momentum effects. Boundary condition violations and the behaviour of implied volatility spreads are examined following 60-day positive and negative returns and produce evidence supporting the momentum effect in the FTSE100 options market. Overall, the findings of this chapter support those of Amin, Coval and Seyhun (2004) in inferring a role for demand in option pricing.

Tests for short-run overreaction, conditional on sharp changes in the FTSE100 over a preceding 5-day period, fail to provide compelling evidence that the UK index options market overreacts. Hence, little support is offered for the findings of Gettleman, Julio and Risik (2011). As a consequence, this chapter provides no motivation to construct a portfolio of FTSE100 options and underlying stocks to test whether it is possible to generate systematic profits.

Ultimately the achievement of this thesis has been to provide a thorough analysis of behavioural finance in the context of options market behaviour in the UK. The empirical results suggest that behavioural biases exist in UK markets but that the market tends towards efficiency.

6.2 Future Research

This thesis has provided numerous insights into investor behaviour in UK markets and consequently provides an important contribution to the literature. It is imperative that this thesis provides a foundation for future research. For example, exchange-traded options in other European markets and markets further afield provides a rich source of data for broader analysis. If a Euronext.LIFFE database could be produced that disaggregates data in a similar way to that provided by the CBOE it would provide the opportunity for a huge step forward in investigating the behaviour of market participants with varying degrees of sophistication. Furthermore there may be insights into momentum and overreaction effects in equity option data which cannot be found in index option data.

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Appendix 1: Cox, Ross and Rubinstein (1979) Binomial Asset Pricing Model

The Cox, Ross and Rubinstein model has considerable merit in pedagogy and overcomes the Black-Scholes limitations in pricing American-style options. The starting point for their binomial asset pricing model is a simple market containing 2 assets, the underlying and riskless asset, and 2 possible states of the world given by:

$$u = e^{\sigma\sqrt{\Delta t}} \qquad \text{(A1.1a)}$$

$$d = e^{-\sigma\sqrt{\Delta t}} \qquad \text{(A1.1b)}$$

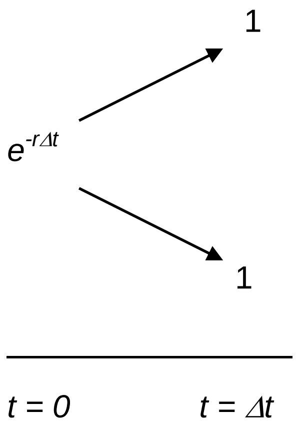
Cox, Ross and Rubinstein demonstrate that, in the absence of arbitrage, a European call option may be accurately priced as follows. Assume the underlying asset follows a binomial process:

$$\begin{tikzcd} & u.S_0 \\ S_0 \arrow[ur] \arrow[dr] & \\ & d.S_0 \end{tikzcd}$$

$t = 0$ $\qquad$ $t = \Delta t$

S_0 denotes the price of the asset at the initiation of the contract. The price at $t = \Delta t$ will be either $S_u = u.S_0$ or $S_d = d.S_0$.

The risk free asset pays £1 at $t = \Delta t$ regardless of which state of nature prevails.



The risk free asset may be viewed as a zero-coupon bond with face value = £1. Purchasing a zero-coupon bond for £$e^{-r\Delta t}$ at t = 0 will yield $e^{-r\Delta t} \times e^{r\Delta t} = 1$ at t = Δt. If a constant, continuously compounded risk free rate is assumed. Then d, u and r satisfy:

$$0 < d < 1 < e^{r\Delta t} < u \qquad \text{(A1.2)}$$

Although actual stock price movements are considerably more complex than those implied by the binomial asset pricing model, the binomial model is valuable in that it approximates continuous time models when sufficient, increasingly small, time steps are used.

Depending on which state of the world prevails at time $t = \Delta t$, a European call option will have different values denoted c_u and c_d.

$$\begin{tikzcd} & c_u \\ c_0 \arrow[ur] \arrow[dr] & \\ & c_d \end{tikzcd}$$

$t = 0$ $\quad$ $t = \Delta t$

In order to price the option, at time t = 0 a no-arbitrage portfolio is constructed which contains:

- One underlying asset S_0

- ϕ European call options c_0

The value of the portfolio is

$$V_0 = S_0 + \phi c_0 \tag{A1.3}$$

There are two possible positions at $t = \Delta t$:

$$\begin{tikzcd} & V_u = uS_0 + \phi c_u \\ V_0 \arrow[ur] \arrow[dr] & \\ & V_d = dS_0 + \phi c_d \end{tikzcd}$$

$t = 0$ $\quad$ $t = \Delta t$

The value of ϕ is selected so as to make the no-arbitrage portfolio risk free, that is, it yields a risk free rate of return $e^{r\Delta t}$. Therefore, the no-arbitrage condition is:

$$V_u = V_d = V_0 e^{r\Delta t} \tag{A1.4}$$

or equivalently

$$uS_0 + \varphi c_u = dS_0 + \varphi c_d = \left(S_0 + \varphi c_0\right) e^{r\Delta t} \tag{A1.5}$$

This may be re-arranged to:

$$\varphi = \frac{S_0(u-d)}{c_d - c_u} \leq 0, \quad c_u \geq c_d$$
$$and$$
$$c_0 = e^{-r\Delta t}\left\{\frac{e^{r\Delta t} - d}{u-d} c_u + \left[1 - \frac{e^{r\Delta t} - d}{u-d}\right] c_d\right\} \tag{A1.6}$$

The coefficient ϕ indicates the number of call options necessary to include in an arbitrage portfolio containing one asset. The negative sign of ϕ implies that a short position in calls is required to hedge a long asset portfolio. Thus, ϕ is the number of call options written to make the portfolio risk-free.

A similar procedure is followed to find the long asset position when one call has been written. The inverse of ϕ is taken and its sign reversed. This gives the hedge ratio or delta of the call option.

$$\Delta = -\frac{1}{\varphi} = \frac{c_u - c_d}{S_u - S_d} \geq 0 \tag{A1.7}$$

The no-arbitrage result for c_0 in can be presented more parsimoniously by defining Q, the risk-neutral probability, as:

$$Q \equiv \frac{e^{r\Delta t} - d}{u - d} \tag{A1.8}$$

The price of a European option is given as its expected value computed using risk-neutral probabilities Q and (1 – Q) discounted at the risk free rate of interest. The Cox, Ross and Rubinstein formula for a single period may be presented as:

$$c_0 = e^{-r\Delta t}\left[Q.c_u + (1-Q).c_d\right] \tag{A1.9}$$

Equation (A1.9) may then be generalized to multiperiod settings, where for each node:

$$c_n = e^{-r\Delta t}\left[Q.c_{n+1}^{(u)} + (1-Q).c_{n+1}^{(d)}\right] \tag{A1.10}$$

The model may be adapted to consider an underlying asset that pays a continuous dividend yield, q. The risk-neutral probability Q is modified accordingly.

$$Q \equiv (e^{(r-q)\Delta t} - d)/(u-d) \tag{A1.11}$$

In order to price American-style options, the model needs to be modified in order to consider the possibility of early exercise. The appropriate model is:

$$P_n = \max\left[K - S_n, e^{-r\Delta t}\left(QP_{n+1}^{(u)} + (1-Q)P_{n+1}^{(d)}\right)\right] \tag{A1.12}$$

Appendix 2: The Heston (1993) Model as Applied to the Tests of Poteshman (2001)

Heston (1993) derived a closed-form solution for the price of a European call option written on an asset with stochastic volatility. His model allows the underlying asset's returns and volatility to be correlated. The model relaxes the Black-Scholes assumption that continuously compounded stock returns are normally distributed. The inclusion of correlation in Heston's model has important impacts on skewness.

The model can be described by the set of equations given in (A2.1):

$$\frac{dS_t}{S_t} = \mu(S_t, V_t, t)dt + \sqrt{V_t}dW_t^S$$
$$dV_t = k(\theta - V_t)d_t + \eta\sqrt{V_t}dW_t^V$$
$$Corr(dW_t^S, dW_t^V) = \rho$$
$$\lambda(S_t, V_t, t) = \lambda V_t \tag{A2.1}$$

Where $r = \delta$ and $k, \theta, \eta, \rho, \lambda, r \,\&\, \delta$ are constants. The underlying asset at time *t* and its instantaneous variance are denoted by S_t and V_t respectively. The set of equations is driven by wiener processes that are correlated with coefficient ρ. The market price of variance risk is represented by $\lambda(S_t, V_t, T)$ and r is the riskless borrowing and lending rate. δ is included as the underlying asset is assumed to pay a continuous dividend yield.

Heston examined the kurtosis and skewness of the closed-form solution for European-style call options and concluded that, if the volatility is uncorrelated with returns on the underlying asset, increasing the volatility of volatility increases the kurtosis of the spot return but does not increase the skewness. Random volatility is associated with increases in the prices of deep in- or out-of -the-money options relative to near-the-money options. If volatility is correlated with returns on the underlying asset then skewness occurs. Positive skewness is associated with increases in the prices of out-of-the-money options relative to in-the-money options. Heston added that it is essential to properly choose the correlation of volatility with spot returns as well as the volatility of volatility.

Appendix 3: Constituents of Equity Portfolio of Financial Stocks with Associated LIFFE Exchange-Traded Equity Options

Company	Code	Category
3i Group PLC	III	Financial Services
Aviva PLC	CUA	Insurance
Barclays PLC	BBL	Banks
HSBC Holdings PLC	HSB	Banks
Land Securities Group PLC	LS	Financial Services
Legal & General Group PLC	LGE	Insurance
Lloyds Banking Group PLC	TSB	Banks
London Stock Exchange Group PLC	LSE	Financial Services
MAN Group PLC	EMG	Financial Services
Old Mutual PLC	OMT	Financial Services
Prudential PLC	PRU	Insurance
Royal Bank of Scotland Group PLC	RBS	Banks
RSA Insurance Group PLC	RYL	Insurance
Standard Chartered PLC	SCB	Banks