Imperial College
Business School

The Implications of Investor Behaviour to Financial Markets

Lisa Desiree Majmin

Submitted in part fulfilment of the requirements for the degree of
Doctor of Philosophy in Finance and Accounting March 2012

Abstract

Financial markets are subject to sentiment from within and beyond their nation's borders. Fund flows either flood markets with liquidity, or drain them to the point of asset fire sales. This typically occurs in accordance with investors' beliefs and risk preferences and ultimately renders markets unstable. This thesis serves to establish the implications of investor behaviour to financial markets. Chapter 2 proposes macro sentiment as a leading indicator for financial instability within the Early Warning Framework of Borio & Lowe (2002). This signalling method identifies imbalances within the financial system. Key indicators include real equity and property prices, and private credit. Macro sentiment is then shown to display excess pessimism prior to systemic crises and therefore, is a relevant leading indicator.

US institutional investor sentiment is measured through the demand for portfolio insurance in Chapter 3. Shefrin (1999) advocates index option markets as the manifestation of institutional investor sentiment. A decrease in index option skewness is associated with bearish sentiment. This chapter applies a non-parametric method to extract the risk-neutral distribution to gauge sentiment based on the 30-day probability of the underlying reaching the at-the-money futures level, and the third moment. These measures are examined in relation to the VIX, the put–call ratio, the slope of the implied volatility function and the Bakshi, Kapadia & Madan (2003) skew.

Chapter 4 proposes a theory of sentiment propagation and examines the link between global and investor sentiment within the US. An extensive literature review of mutual fund flows and sentiment within the broad context of the macroeconomy affirms the use of cross-border fund flows as the channel through which sentiment propagates. The empirical section then establishes congruency between global sentiment, as measured by dedicated USA equity and bond fund flows of US and non-US domiciled investors and sentiment within the US.

Acknowledgements

I would like to thank my supervisor Dr Lara Cathcart for continued support and encouragement. I am also grateful for the support of co-supervisor Dr Lina El-Jahel, my family and my dearest friend Clive Katz.

Dedication

In loving memory of my grandmother Fay Varejes – the epitome of strength.

‘Money may make the world go round, but sentiment can make it spin.’

L.D. Majmin

Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Motivation

'Action is Eloquence.'

William Shakespeare

Behavioural finance has emerged to rationalise those anomalies within financial markets that may appear irrational. Although it is often associated with investor psychology at the individual level, the breadth spans research which pertains to behaviour in the aggregate; the latter of which is relevant to this research. Ultimately, it is the synchronicity of the collective that spawns widespread panic during moments of extreme uncertainty, and 'irrational exuberance' in boom periods. These bipolar phenomena are neither novel nor confined to any particular market. Yet the means to contain either remains an enigma. Central banks are autonomous in their endeavour to maintain a range of financial stability. The increasingly integrated nature of financial markets renders this task more challenging. Domestic economies are therefore susceptible to the behaviour of investors both within and beyond their domicile.

Sentiment within financial markets remains illusive with respect to definition and quantification. Therefore, scepticism pertaining to its incorporation into traditional asset pricing models remains. Debating market efficiency is superfluous as evidence that suggests otherwise is plentiful. Divergence from this theory results in predictability, excess volatility and asset price bubbles, within financial markets. Hence the pertinence associated with the accurate specification and measure of sentiment is addressed. In particular, this thesis distinguishes between frequency and therefore, applicability to a reference group. The proposition that consumer confidence is a measure of *macro sentiment* is addressed in Chapter 2. The assumption that institutional investor sentiment is a manifestation of their behaviour is central to both Chapters 3 and 4.

Contrary to research which attempts to forecast aggregate market returns using proposed sentiment measures, this thesis reconciles both the localised and global effects of sentiment. A unifying theory of sentiment which extends both the domain of influence as well as the associated impetus, is the quintessence of the combined chapter contents. The apprehension of financial instability and its contagion is a fundamental endeavour which should embrace the inclusion of sentiment, considering its prominence as a facilitating factor.

In order to proceed, clarification of the term *sentiment* is required.

Definition 1.1 *Macro Sentiment refers to the survey-based measures of consumer sentiment, reported monthly. This is an aggregation of responses to questions posed to a representative group of society, referenced as the consumers of the relevant country.*

Within financial markets, the group of investors that will be of relevance are the institutions. Investor sentiment refers to the outlook of investors that participate within financial markets. This is further decomposed into retail and institutional investor sentiment.

Definition 1.2 *Institutional investor sentiment reflects the current and near-term perceptions of the aggregate stock market performance. The measurement thereof is to be deduced from trade decisions regarding portfolio insurance using index options. This has been substantiated by Shefrin (1999). Thus, the acquisition of portfolio insurance, using equity index put options, is regarded as a bearish sentiment as investors fear markets may fall at the option expiry.*

A 30-day forward-looking measure will be constructed in 3; the nearest maturity option series are used in 4. This is done to capture the more immediate outlook of the investor group.

1.2 Contributions

1.2.1 Macro Sentiment as a Leading Indicator for Financial Instability

Chapter 2 proposes the use of *macro sentiment*, synonymous with consumer sentiment, as a leading indicator for financial instability within the United States and the United Kingdom. The Early Warning System (EWS) of Borio & Lowe (2002) is the reference framework which monitors the buildup of imbalances in a given economy as a means to forewarn against impending instability. Justification for inclusion is broached by reviewing the merits of macro sentiment with regards to both the real economy and aggregate equity market. By reviewing bilateral trade-related data in conjunction with macro sentiment, a channel through which macro sentiment may be 'exported' is revealed. Furthermore, macro sentiment within the context of the EWS displays excess pessimism prior to the identified systemic crises. Thus, sentiment here is a measure which primarily encompasses current and expected opinions with respect to the real economy. Financial markets affect this measure insofar as expected labour income and, to a lesser extent wealth, is concerned.

This chapter contributes to the literature by establishing a link between macro sentiment of individual countries indirectly via trade strength examining Granger-causality over the relevant time period. The main contribution is the validation of the use of macro sentiment as a leading indicator within the EWS. Thus, this chapter establishes the significance of sentiment as a means to forecast financial instability, pertaining to banking crises. Contagion between countries is also addressed as sentiment contagion is shown to be affected by significant bilateral trade relations.

1.2.2 Institutional Investor Sentiment: The Options

Chapter 3 examines sentiment within financial markets which is specific to institutional investors. Shefrin (1999) discusses inefficiencies which persist within index option markets as a consequence of heterogenous beliefs. Given that index put options are tantamount to portfolio insurance, increases in demand tend to increase the cost of the associated hedge portfolio and consequently, the implied volatility of that option. Index options are therefore the primary market wherein sentiment can be gauged due to the attributes of limited liability, leverage and upside. The information to be gleaned from the option-implied risk-neutral density of the underlying index renders it suitable for the construction of a forward-looking investor sentiment measure: The daily 30-day forward measures of the cumulative probability attached to the index reaching the current at-the-money futures level, the risk-neutral skew and the smirk (the difference between the out-the-money put and the at-the-money call implied volatilities) are extracted on a given trading date. The United States (US) aggregate equity market – the S&P 500 index and associated European index options – is the reference market; the implied measures are then examined with respect to the CBOE VIX, the model-free risk-neutral implied skew of Bakshi et al. (2003) and the weekly Investors Intelligence institutional investor sentiment survey. The relationship to the daily return completes the analysis as a means to decipher the dynamics of the related measures.

This chapter contributes to existing sentiment literature by asserting that daily institutional investor sentiment can be measured by examining the demand for portfolio insurance. The fully non-parametric method of Bondarenko (2003) is then applied to index options to extract the risk-neutral distribution of the underlying index at maturities that are conducive to finding the 30-day forward measure. The interpolated distributional measures are identified as the sentiment of institutional investors: The implied skew and probability measure are explored with reference to other related variables over the period January 2005 to October 2010. Particular emphasis is placed on the turbulent market regime that characterised the latter half.

1.2.3 Sentiment Propagation and Portfolio Insurance

Chapter 4 contributes to the literature by proposing a *Theory of Sentiment Propagation*. The premise to be established is that sentiment propagates via cross-border fund flows. A broad literature review, which encompasses empirically established relationships between the macroeconomy, financial markets and the integration thereof, and fund flows, constitutes the justification thereof. Chapter 2 alludes to the means through which sentiment diffuses between the macroeconomies of countries. The lag effect embodied within trade relationships deems macro sentiment ineffectual with respect to high-frequency financial markets.

The positive feedback effect between mutual fund flows and the returns of both the aggregate equity market and associated funds has been studied extensively for US funds. Variations in the source data and therefore, investor group, the time period as well as data frequency, have led to conflicting results. Regardless, it is the action of allocating funds to cash, bonds or equity (or alternative asset classes not discussed here) that embodies the subjective risk preferences and beliefs of expected performance.

Limited research exists which explores cross-border fund flows due to data constraints; access to a global fund flow dataset permits such analysis. This chapter incorporates the use of the Emerging Portfolio Fund Research dataset which will be further discussed in the empirical section. Fratzscher (2011) documents both global and country-specific factors which account for equity and bond fund flows specific to the global financial crisis of 2008, with the insight of this data. Distinguishing between advanced and emerging economies, the author documents that global factors were accountable for a sizeable portion of fund flows during the crisis regime. Global common shocks included the TED spread, the VIX and macroeconomic news.

The second contribution of this chapter associates institutional investor sentiment within the US, as measured by the option-implied skew derived in Chapter 3, and *global* sentiment. Here, global sentiment refers to both equity and bond fund flows of US and non-US domiciled institutional investors, derived from this dataset. The hypotheses which are empirically proven relate increases in bond fund flows to that of portfolio insurance, and positive continued performance of equity funds to a reduction in the demand for insurance.

The integration of financial markets is accompanied by enhanced capital mobility; Laeven & Valencia (2008) and Kaminsky & Reinhart (1999) decree that financial crises have often arisen due to velocity of fund flows. Emerging market economies are particularly susceptible to these forces. Sentiment may well appear to be nebulous in concept; yet in context, it is definitive.

Chapter 2

Macro Sentiment as a Leading Indicator for Financial Instability

2.1 Introduction

Financial crises are not unique to any particular period of time; history is replete with episodes of banking and currency crises. The severity is usually determined by the associated cost as measured by loss in output and fiscal outlays required to restore the financial sector health. Often, contagion effects cannot be avoided as spillovers to other countries occur via capital flows; financial contagion has been particularly relevant in the most recent subprime crisis. Market crashes and bank failures adversely affect the real economy as funds are diverted to contain further spillover rather than being allocated efficiently within the real economy. Sharp equity market declines result in the erosion of corporate wealth as represented by listed equity, due to a loss in confidence (investor sentiment) which may or may not be associated with fundamentals. Borio (2006) cites financial liberalisation (increased integration of global financial markets) as well as innovation as being responsible for the more recent episodes (since the 1990s). Financial liberalisation facilitates the access to credit which thereby creates a perception of wealth and is often supported by external funding. In particular, cross-border fund flows may either be directed at equity markets, particularly those emerging economies which have output growth in excess of developed markets, or bond funds which, due to sovereign credit ratings and inflation, yield higher nominal returns. Monetary and foreign exchange policy is highly relevant as a determining factor in the ability to attract funds. Fund flows are indicative of the confidence associated with the fundamentals as well as ability to generate returns. This will be further explored in Chapter 4.

Globalisation has created an environment whereby investors' risk appetite has a critical effect upon emerging markets as capital repatriation manifests in the flight to dollar-denominated assets, resulting in large-scale losses and currency depreciation during financial crises. Investors have the ability to either drain liquidity or create excess demand, thereby inflating prices to unprecedented levels, both within and across borders. Doing so not only affects the immediate financial sector; the onset of widespread panic and a loss of confidence filters through to the real economy as a result of wealth depreciation. Ultimately, it is the self-reinforcing cycles which then lead to inflated asset prices, loose external financing constraints, increased output and reduced perceptions of risk. For a prolonged period of time, this cycle reinforces and amplifies imbalances within the domestic economy and so too strain within the financial system. The requirement for regulatory intervention may lead to such an instance being deemed one of *financial instability.*

It is imperative to have a well-defined notion of financial stability in order to facilitate the identification of weakness within an economy and ultimately, direct policy towards obtaining such an objective (Schinasi 2004). Thus stability is determined by the indirect adverse affects on the real economy. At first blush, one might be persuaded that stability refers to a low-volatility environment within financial markets and relatively benign inflation rates. However, finance as a sector is composed of many interlinked elements which include infrastructure, institutions, and markets. Consequently, financial stability is determined by the aggregate condition associated with each of the constituent parts, conditional of those relationships; Schinasi stipulates it is determined by 'the soundness of financial institutions, financial markets conditions, and effectiveness of the various components of the financial infrastructure'.

Definition 2.1 *A financial system is in a range of stability whenever it is capable of facilitating (rather than impeding) the performance of an economy, and of dissipating financial imbalances that arise endogenously or as a result of significant adverse and unanticipated events.*

This definition is subject to the context of a monetary economy wherein (fiat) money is used as a means of exchange for goods and services. Additionally, Schinasi notes that money may not in general be the most efficient store of value, with the exception of the imminent future or periods of financial distress. Thus, financial engineering has created preferred substitutes that oblige with 'temporary and reversible intertemporal means-of-payment and store-of-value services'. Schinasi acknowledges that 'finance enlarges society's opportunities for, and efficiency in, intertemporal economic processes such as trade, production, wealth accumulation, economic development and growth, and ultimately social prosperity'. It is the universal acceptability of money and the existence of a smooth-functioning financial system that creates an environment conducive to social prosperity. Implicit in the field of finance is the inherent risk associated with the counterparty and therein, that of default. This is precluded in a fiat system (assuming the government has backed the currency). Hence, finance has evolved to facilitate the use of fiat money. However, it is trust and the betrayal thereof which is alluded to as an origin of financial instability, thereby affecting both individual and social welfare. In particular, Schinasi asserts that the propagation of the lack of trust may ultimately lead to systemic and widespread financial instability. Containment is subject to this process which may then spill over into the real economy. Yet disturbances within financial markets need not lead to financial instability; closing of financial institutions, the increase in volatility or turbulent conditions within markets may arise from competitive forces. Thus, in the absence of contagion and systemic effects, such developments may be favourable.

The *range of stability* in this definition refers to the continuum of quantifiable variables that reflect the efficiency of finance with respect to 'savings and investment, lending and borrowing, liquidity creation and distribution, asset pricing, and ultimately wealth accumulation and growth'. *Facilitating* the performance of an economy specifically refers to the promotion of efficient allocation of real resources, the rate of growth of output, and the processes of saving, investment, and wealth creation. This definition clearly indicates the financial system may impede the performance of the economy *endogenously*, through the 'accumulation of imbalances which may be a result of asset mispricing or other imperfections'. In particular, the author notes that banking systems are proven to be vulnerable to such imbalances (credit-risk concentrations or illiquidity).

In contrast to price stability, financial stability cannot readily be quantified. Developments in financial instability are inherently difficult to forecast due to contagion effects and nonlinearities in the relationships between certain variables. Therefore, a forward-looking approach is required to establish the buildup of imbalances. Hakkio & Keeton (2009) propose the Kansas City Financial Stress Index (KCFSI) which may signal the requirement for central bank intervention during periods of financial stress. A clear definition thereof remains illusive as each occurrence is unique.

However, the disruption to financial markets is associated with some of the following phenomena: Increased volatility reflects the increased level of uncertainty of market participants pertaining to expected future cash flows. This is then considered Knightian uncertainty as risk cannot accurately be determined. Uncertainty regarding the behaviour of other investors contributes to market volatility as market participants are forced to act based on 'what average opinion expects average opinion to be', as John Maynard Keynes had discussed in his 1936 book 'The General Theory of Employment, Interest and Money'. Hence asset prices become distorted and further disconnected from fundamentals as investor sentiment dominates trading activity. The 'flight-to-safety' also characterises such episodes as risk appetite decreases and investors' are less likely to want to be in possession of relatively risky assets. This may be due to an altered sense of the inherent risk. The requirement for liquidity to meet margin calls or increase cash holding results in portfolio rebalancing as investors are forced to sell illiquid assets. [1] This will be further addressed in Chapter 4.

According to IMF World Economic Outlook (1998), there are a number of different categories of crises which all have common origins: The buildup of unsustainable economic imbalances and misalignments in asset prices or exchange rates. A *currency crisis* is characterised by a devaluation, or if the authorities are forced to defend the currency by expending large amounts of foreign reserves or raising interest rates relatively high. A *banking crisis* refers to an instance wherein potential or actual bank runs or failures induce banks to either suspend the internal convertibility of their liabilities or which compels the government to intervene to prevent this on a large scale (contagion thereof). This may assume systemic proportions. *Systemic financial crises* are severe disruptions of financial markets that impair the market's ability to function effectively and may have extreme adverse effects on the real economy. 'A systemic financial crisis may involve a currency crisis, but a currency crisis does not necessarily involve serious disruption of the domestic payments system and thus may not amount to a systemic financial crisis.' A *foreign debt crisis* is a situation in which a country cannot service its foreign debt, whether sovereign or private. The magnitude of the imbalances and ultimately the correction thereof, determine whether a crisis will ensue. Crises are often triggered by a sudden loss of confidence in the banking or currency sector. Indicators thereof may be able to forewarn against such

[1] The variables included in the KCFSI are: three-month LIBOR/three-month T-bill spread (TED), two-year swap spread, off-the-run/on-the run 10-year Treasury spread, Aaa/10-year Treasury spread, Baa/Aaa spread, high-yield bond/Baa spread, consumer ABS/five-year Treasury spread, negative value of correlation between stock and Treasury returns, implied volatility of overall stock prices (VIX), idiosyncratic volatility (IVOL) of bank stock prices and cross-section dispersion (CSD) of bank stock returns.

occurrences. Thus, such measures are of interest in the determination of decreasing confidence or extreme levels of optimism associated with boom periods.

The monetary regime that reigns, the level of government regulation and the participation of investors and consumers, ultimately determine the configuration of the economy at any particular point in time. This is likely to be influenced by both trade and capital flows to varying degrees, relative to the strength of those relationships. Monetary policy has evolved to maintain price stability as a primary concern and in some cases contain and reduce unemployment levels whilst promoting output growth. This is therefore attuned to the facilitation of financial stability, insofar as the remit allows, which results in the effective operation of the real economy. Avoiding references to detailed economic theory, one can speculate that at a minimum level of unemployment and inflation and acceptable productivity, the economy is deemed to operate at an equilibrium level, quantified by output, the consumer price index, unemployment and various other macroeconomic data. However, it is the collective behaviour and participation of those agents within the economy and financial markets which ultimately yields this equilibrium. The term *animal spirits* was proposed by Keynes, as one of the fundamental determinants of economic prosperity. Confidence is indicated to resemble 'naïve optimism'. Thus, the remit of central banks is ultimately to ensure that the citizens of the country at large are confident about the current future course of the economy. One may then assert that confidence is likely to be a key determinant of the future course of the economy, and therefore a key qualitative measure to establish the likelihood of future economic activity.

Consumer sentiment is a qualitative survey-based measure of confidence which reflects on aggregate, the current and expected future developments of the relevant economy. [2] Monthly surveys are conducted in most developed (and some emerging) economies as a means to gauge the general mood of society. Questions are directed to ascertain levels of well-being pertaining to both self, and the economy at large. Katona (May 1968) developed the consumer sentiment survey in 1946 which was based on a rationale from psychological economics: this proposes that a household's response to a change in income or wealth depends upon its attitudes at the time. This measure of sentiment was intended to capture consumers' willingness and ability to buy. Spending refers to discretionary purchases, whilst willingness refers to consumers' assessments of their future income prospects. Discretionary purchases are those items than can be postponed such as homes,

[2] In particular, the University of Michigan Consumer Sentiment Index address concerns which pertain to personal finances, business conditions, and buying conditions.

vehicles and household durables. These are large, infrequent, usually planned and involve credit. He suggested that spending increases with optimism whilst precautionary saving increases with pessimism. Katona notes that confidence represents the uncertainty associated with future income streams, and therefore encompasses both the expected level and variance of future income. Katona argues that the attitudes that enter into consumer sentiment are more than a reflection of the current state of the economy and are not necessarily related to current economic variables in any stable way. Attitudes may be influenced by political and economic events that are not quantifiable. Additionally, similar economic or financial developments may be perceived differently under different circumstances. Particularly at turning points, consumer willingness to buy may be a significant and unpredictable independent factor which determines spending.

One interpretation of the index is that it unequivocally measures consumers' perceptions of the probability of financial distress (Mishkin, Hall, Shoven, Juster & Lovell 1978). Consumer durables are perceived as illiquid assets, and therefore any apprehension of financial distress implies a reduction of such purchases. A decline in the index might suggest that consumers have perceived a rise in the likelihood of financial distress and would prefer holding liquid financial assets rather than illiquid consumer durables. The illiquid aspect of consumer durables, and not their discretionary nature, is likely the reason why consumer sentiment may indeed be useful for forecasting such distress. In particular, the assertion is such that sentiment can be used as a leading indicator of financial instability within that country. Curtin (2007) notes that 'surveys are based on the premise that data on consumer expectations represent a leading indicator of future changes in the macro economy'. The current research will be primarily concerned with the consumer confidence indices of the United States (US) and the UK as a measure of macro sentiment. Contagion between countries is not to be dealt with.

To further substantiate the relevance of macro sentiment, section 2.2 addresses literature which empirically establishes that financial asset price inflation which reflects boom periods within these markets, leads to increased optimism via a confidence channel. This is in addition to the traditional wealth effect, the strength of which tends to differ between countries and regions. The relationships between the macroeconomy, confidence and financial markets is also addressed in Chapter 4 in the *Theory of Sentiment Propagation*. Pertinent to the current research are the relationships between confidence and real estate, and between confidence and the aggregate stock market. Having mentioned the implications of confidence to discretionary spending, it then follows that private credit provides the liquidity to aid such purchases. The easier the access, the more likely the possibility of a boom associated with those purchases is. Hence real estate is an asset class that may manifest the consequences of consumer confidence.

Given that financial instability is often associated with exuberant financial market valuations – which may appear to be disconnected from fundamentals at times – and the subsequent reversal thereof, consumer sentiment may be an apt measure to capture the momentum of market appreciation. These themes are closely tied to the debate regarding the extent to which monetary policy should intervene in asset markets, if at all. As mentioned by Crockett (2003), 'In a monetary regime in which the central bank's operational objective is expressed exclusively in terms of short-term inflation, there may be insufficient protection against the build up of financial imbalances that lies at the root of much of the financial instability we observe'. Hence, benign financial conditions, which are considered low-inflation environments, do not preclude the buildup of imbalances. Thus, in a framework which serves as an early warning system for impending instability, it is instrumental to incorporate signals which pertain not only to the identification of imbalances (credit, asset price inflation) which reflect fundamentals, but also that which measures the macro sentiment of the aggregate market.

The current research references the early warning system (EWS) of Borio & Lowe (2002) (BL) to detect periods of financial instability up to three years in advance of impending episodes, which are signalled by the level of imbalances. This is conducted using historical episodes of instability which have been identified. The EWS is an adaptation of the signalling approach laid out in Kaminsky & Reinhart (1999) (KL) in which leading indicators are selected as a means to forewarn against the 'twin crises' – banking and currency crises. The objective is to identify the accumulation of financial imbalances which can, and do, occur in a low-inflation environment. Financial distress accompanies the unwinding of financial imbalances that build up during benign financial conditions. The financial cycle can amplify, and is amplified by, the business cycle, as booms and busts in asset prices as well as rapid credit expansion can lead to future instability. BL note that price stability may promote financial stability yet it also increases the likelihood of excess demand pressures which may appear in credit aggregates and asset prices, rather than goods and services. In addition to this, the credibility of the policymakers' commitment to price stability in a low-inflation environment obviates the need to tighten monetary policy which permits such a buildup of imbalances. Therefore, the ex ante identification of the cumulative process of financial and real imbalances may then forewarn against future financial distress. There is an undeniable urgency to research financial instability; Central banks, the International Monetary Fund (IMF), the World Bank and the Bank for International Settlements (BIS) have published numerous reports dedicated to the advancement of the topic. Leading indicator models, which are either qualitative response models or of the signalling approach, have been proposed from both microeconomic and macroeconomic perspectives.

The extension to the BL EWS for each country includes the imbalance associated with house price inflation, and the effect of macro sentiment. BL discuss both commercial and residential property booms within their analysis, however do not include relevant indices in their assessment. [3] Given that the growth in private credit and the (residential) property boom in the US have been ex post oft-cited signals associated with the recent subprime crisis, the inclusion of both private credit and the house price index for the US and UK will be relevant leading indicators. This research therefore contributes to the EWS macro framework by incorporating macro sentiment as a leading indicator. Data to be examined to detect imbalances for each country are the ratio of private credit to GDP, real credit (private credit deflated by the consumer price index, CPI), real aggregate asset prices which are the inflation adjusted nominal indices of the S&P 500 (US) and the FTSE 100 (UK), real house price indices and macro sentiment.

The hypothesis asserts that the addition of macro sentiment into an EWS for the relevant country improves the signal which forewarns of financial instability up to three years in advance. Sentiment has marked effects within both the real economy and financial markets as consumers and investors are the active participants. The performance of the economy is therefore a manifestation of sentiment to some extent. Financial markets also affect the real economy indirectly through the macro sentiment of the population; the stock market shifts prospects for employment income as well as the values of nonfinancial and financial assets. Therefore, including macro sentiment may yield a better and more complete portrayal of the macroeconomy. Diamond & Dybvig (1983) incorporate the role of sentiment within a model of bank runs: shifts in investors' risk expectations explain irrational behaviour of consumers running on banks. In the model, the instability results from the existence of two equilibria: the continuation of the status quo of an unimpaired relationship between depositors and the fundamentally sound bank, or that of a bank run due to ambient fear contagion and consequently, simultaneous withdrawals. Individual bank

[3] In a slightly updated version, Borio & Drehmann (2009) do include these assets.

failure may spread due to contagion associated with asymmetric information and, hence, bank crises are systemic (Davis & Karim 2008).

This chapter is organised as follows. Section 2.2 explores macro sentiment within the US and UK. A digression into the means by which macro sentiment of economies may be linked is also addressed in section 2.2.3. Thereafter, the relationship to the aggregate market in the relevant countries is discussed with references to related literature. A literature overview conveys the significance of macro sentiment as an indicator (coincident or leading) within both economies. Concluding remarks render macro sentiment useful as a signal within the EWS to forewarn against impending financial crises. Section 2.3 further examines financial instability. Section 2.3.1 briefly reviews the BL EWS. Empirical results are presented in section 2.4: the US and the UK are to be treated as separate entities as contagion is not addressed within the framework. It can be noted that imbalances that are identified may be due to the influence of externalities which likely do reflect the systemic nature of crises. Data sources herein discussed analysed within the EWS. Section 2.5 concludes and establishes the usefulness of macro sentiment.

2.2 Macro Sentiment

The analysis that follows is restricted to the US and UK. Therefore the University of Michigan Consumer Sentiment Index for the US and the UK Consumer Confidence Barometer, which is conducted by GfK (Growth from Knowledge) NOP on behalf of the European Commission, will be the reference indices. Prior to examining the time series properties in sections 2.2.1 and 2.2.2 respectively, further motivation for the hypothesis which asserts that macro sentiment may be a viable signal as a leading indicator within the EWS is explored below. The case will be shown to be plausible in so far as the effects on the macroeconomy can be established as well as the information content therein; there is naturally a vast amount of research which explores these relationships. Some papers make use of alternative indices such as the Conference Board Consumer Confidence Index for the US and the Gallup Poll in the UK.

Throop (1992) analyses the causes and effects of consumer sentiment within the US, referencing the University of Michigan Consumer Sentiment Index (CS^{US} henceforth). Throop notes that the index has previously led business cycles, and three of its components are included in the Commerce Department's Index of Leading Economic Indicators. Addressing whether sentiment contains unique information (in relation to that of economic variables) which may forecast consumption spending, Throop finds that changes in sentiment are generally caused by purely economic factors. Sentiment bears a stable relationship to just a few economic variables; these include expenditures on consumer durables, spending on nondurables and services, personal disposable income, and interest rates as represented by the six-month commercial paper rate. Consumer sentiment reflects economic adversity or prosperity and reinforces rather than initiates business cycles. The index can however move independently from current economic conditions during abnormal circumstances, such as the Gulf War.

Three main views on consumer sentiment which have emerged in the literature are mentioned. The first is the original opinion of Katona which states that sentiment is an important predictor of spending on discretionary items (consumer durables). However, as a measure it is not believed to be adequately represented by responses to any single question or to bear any stable relation to aggregate economic variables. Thus, the survey of a set of questions is deemed necessary to accurately forecast consumer spending on durable goods. The second view is that sentiment mainly measures optimism or pessimism about future economic conditions. In 'permanent income' theories of consumption, current spending on nondurables and services, as well as on durables, depends on expected future income. The sentiment index may provide a better measure of this than conventional modelling based on past observations of incomes. The third view is considered the most useful aspect of the index as a measurement of the uncertainty or risk, associated with the likelihood of job loss and/or severe income loss and attendant financial distress. A higher probability of financial distress would lead an individual household to save more in liquid form and less in illiquid form to cover a possible future shortfall in future income. The most effective way to do this would be to postpone expenditures on consumer durables rather than on nondurables and services. In this view, the most important dimension of the index is its measurement of confidence or mistrust, rather than optimism or pessimism.

Fuhrer (1993) seeks to determine whether sentiment in the US has the impetus to influence the fate of the economy, this is, can consumer optimism spur prosperity from the depths of recession or alter the course of the economy, regardless of fundamentals. Recalling the 1990 invasion in Kuwait, consumer confidence plunged, as did the desire to spend, irrespective of income and access to credit. Hence, it appears that sentiment independently led to the onset of a recession. The possibility that sentiment either accurately forecasts, or provides an accurate measure of consumers' forecasts, of economic activity is also addressed. Either of these instances is relevant as it is the expectation that will determine consumption behaviour. Sentiment may be merely a reflection of other relevant economic variables which include income, unemployment, inflation and real interest rates, or may be enhanced due to private knowledge of the respondents. Examining data between 1960 and 1992, the author concludes that the index largely reflects macroeconomic aggregates and has a minor role in forecasting one-quarter ahead variation in consumption expenditure. Contemporaneous observations did not yield improved results. However, over the 30-year period, the predictive ability is systematic, and therefore significant and reliable. This arises from the ability to forecast income growth, rather than the direct link between consumption and sentiment.

Matsusaka & Sbordone (1995) present a class of models which exhibit multiple equilibria in which output fluctuates according to expectations; self-fulfilling prophecies may be responsible for or contribute to recessions. Given that this appears to be the case for post-war recessions in the US economy between 1953 and 1988, they seek to establish causality between fluctuations in output as measured using gross national product (GNP) and consumer sentiment. The authors disentangle the relationship in a vector autoregression, including relevant fundamentals. Their assumption is that if 'consumer sentiment can forecast GNP movements even after controlling for fundamentals and other publicly available predictors of output...' then sentiment may in fact affect output. Control variables include government spending, money supply and sensitive material prices, components of the leading indicators, and a default risk variable. Their findings suggest that Granger causality runs from sentiment to GNP. The significance of this result gives credence to the use of sentiment as a macro leading indicator.

Based on surveys of consumers' perception of inflation conducted in the US, Germany and Brazil, Shiller (1997) documents that inflation lowers households' expectation of real income and increases the uncertainty of real income. Households are uncertain of whether or not they will be compensated in the future and this explains the negative relationship with the sentiment index. Housing wealth directly affects households' physical wealth, and hence has a positive impact on sentiment. The precautionary savings explanation of consumption behaviour suggests that the stochastic nature of interest rates directly impacts the uncertainty of future income streams, as it affects households' access to capital markets. This result further signifies that the information contained in macro sentiment as expectations pertaining to income, savings, spending and ultimately wealth, in aggregate, determines the future course of the domestic economy at a given point in time. Naturally, extraneous and unexpected circumstances alter the viewpoint as time elapses.

Delorme Jr, Kamerschen & Voeks (2001) make a comparison between the UK (measured by the Gallup Poll) and US with respect to the relationship between sentiment and the Rational Expectations Permanent Income Hypothesis. This assumes that it is only unexpected shocks which have an effect on future income growth, and consequently further consumption. They find that in the UK, sentiment is affected by current real interest rates, inflation and change in housing wealth. Current real interest rates and inflation have a negative affect on the index, whilst an increase in housing wealth affects it positively. They also find that the measure of sentiment for the US is only significantly negatively dependent on current inflation and the change of current unemployment: unemployment, or the prospect of it, lowers households' expectation of income. Both the US and UK indices take into account prevailing economic conditions which would affect their expected income.

Pain & Weale (2001) examine the information content of consumer surveys in the US and UK (survey conducted by the European Commission which is the seasonally adjusted time series). Examining the UK data, they find there is a tendency for confidence to be weaker in times of subdued growth. The long-run average is below zero which suggests bias in the survey, inappropriate weighting or innate pessimism. They also point to times where sentiment has provided a misleading signal. The index declined (to a level below that of the previous two recessions) in the latter part of 1992 when the UK withdrew from the European Exchange Rate Mechanism even though the forced devaluation of sterling brought about economic recovery. Running regressions to assess the relationship between current expenditure and survey responses in both countries, a significant positive correlation was found between the time series. The CS^{US} contains information which helps predict future expenditure growth in the US; this was not the case for the UK. This is consistent with the above findings. The significance of consumer spending cannot be ignored – according to Curtin (2007), this accounts for between one half and two-thirds of all spending in market-based economies. Therefore, changes in consumer spending behaviour will dramatically affect output. Specifically, in 2005, consumers spent more on homes, vehicles and other durables than firms invested in equipment.

Empirical evidence for the US and for the UK confirms that consumer confidence determines household consumption behaviour over and above the effect of income. Easaw & Ash (2004) state that the aggregate index is deemed a proxy for future income growth. They have also argued that such indices contribute to economic cycles via the impact on cyclical consumption behaviour and, therefore, are of particular interest to monetary authorities when pursuing counter-cyclical policies (Easaw & Ghoshraya 2008).

Berry & Davey (2004) assess the incremental information that may be deduced from UK macro confidence using the GfK barometer (CS^{UK}), in addition to household spending-related data, particularly consumption, over the most recent 30-year period. They find that the correlations between economic variables and confidence generally have the signs expected: positive for income variables, asset prices and GDP growth, and negative for interest rates and changes in unemployment. The effects of standard economic determinants of consumption (earnings growth, the change in the unemployment rate, interest rates, changes in the cost of living as measured by the tax and prices index (TPI), house price inflation, and equity price and exchange rate changes) are filtered out to extract the residual information content; this is perceived to be the reaction to non-economic events. Alternatively, it may reflect the complexity of the aggregate thought process, additional to fundamentally explained results. Examining the residual component, sharp movements in this component are often, but not always, concentrated around key events. Examples include the build-up to the Gulf War (early 1990s), the UK exit from the European Exchange Rate Mechanism and the period following 11 September 2001, and the build-up to the war in Iraq. In some instances, weakness did not pertain to economic fundamentals and the index may have captured concerns relating to a slowdown in house price inflation or an expectation regarding interest rates. They find that it is only the component of confidence in the UK that can be ascertained from the related variables (income, wealth, interest rates), that has any explanatory power for consumption behaviour (spending). Hence, additional information may or may not be discernable given that CS^{UK} on occasion reacts to events unrelated to economic data.

Berry and Davey compare CS^{US} and CS^{UK} to find that although the questions are similar, their short-term movements differ, which may reflect economy-specific factors. With respect to consumption in the US, the results of both explained and unexplained components appear to be significant with respect to consumption, after controlling for income and growth. Results vary according to the methodology of the referenced papers.

Curtin (2007) discusses the process by which surveys are formed and what they in fact represent.

Examining survey measures with respect to their relationship to objective economic measures has taken one of two forms: testing what sources of information consumers used to form their expectations (the inputs of the decision process), and what measures consumer expectations are able to predict (the outputs of the decision process). Whilst most have assumed that these two processes are independent, with expectations typically formed in advance of their use in decision-making, consumers may be more likely to simultaneously form and use expectations. Thus, Curtin asserts that expectations about prospective economic changes should incorporate information about the past as well as provide information about the future. Surveys are critical to the future course of the economy as they access private information, in addition to that which is publicly available and may be incorporated into the survey results. Curtin states that '...it is this private information that represents the independent additional information that is the unique contribution of survey measures of consumer sentiment.'

A series of VAR regressions to test Granger causality between the sentiment index (of the 45 countries included in the sample) and a range of objective economic measures were performed by Curtin; the variables included are thought to be determinants of sentiment such as the unemployment rate, inflation rate, interest rate, and personal income, as well as measures of outcome which include consumption of durables, vehicle registrations, retail sales, total personal consumption and GDP. Variables are defined as the year-to-year percentage change in the price adjusted series, with the exception of unemployment, inflation, and interest rates, which were defined as the year-to-year percentage point change. Five lags of all variables were entered into the regressions. The selection of the variables covers a broad range of both informational inputs and behavioural outputs, and is consistent with previous research. Results indicate that sentiment is statistically significantly related to past changes in economic variables, as well as providing predictive information about future changes in those same variables. Thus, sentiment captures both backward- and forward-looking information. The analysis focused on assessing the overall information content of sentiment, its sensitivity to differences in measurement methodology, and its applicability across a wide range of countries and cultures. Consumers view changes in employment, GDP, or even retail sales as indicators of strength or weakness in the economy and hence influence their level of economic sentiment, and in turn changes in sentiment forecast future changes in those same variables.

In 50% of all countries, there is a significant predictive relationship running from changes in

Table 2.1: Proportion of Granger-Causality tests that indicated a significant relationship for the US and UK (five lags), as reported in Curtin (2007).

Country	Variable predicts Sentiment	Sentiment predicts Variable
UK	33%	44%
US	89%	56%

the unemployment rate to changes in consumer sentiment, controlling for past changes in the sentiment variable. This indicates that unemployment is a powerful determinant of changes in consumer sentiment. It is also the case that in 62% of the countries, a change in sentiment proved to be a significant predictor in forecasting a future change in the unemployment rate, controlling for past changes in unemployment. This result further supports the notion that consumer sentiment largely reflects income expectations as well as the uncertainty about future wage income. The next most significant variable is GDP: Past changes in GDP had a significant impact on sentiment in 59% of the countries, while past changes in sentiment were significantly related to future changes in GDP in 54% of the countries. Given that consumer spending accounts for over half of GDP, these relationships are expected. Regarding the US and the UK, the ability of the macro variables to be predicted by and to predict sentiment appears far greater in the US than in the UK. This can be seen in 2.1.

Thus sentiment contains information about future trends in the macroeconomy. Curtin (2007) states that measures to capture consumer expectations were intended for short-term forecasting; sentiment data is available prior to the remaining macroeconomic data releases and provides independent information about the future course of the economy.

Whilst income and employment prospects are still the main driving force, there is now a greater range of economic variables on which consumers base their decisions. The borders of nation states no longer restrain information flows nor limit the direct purchase of goods or services by consumers. The economic sophistication and knowledge of the population have increased substantially in recent decades. Consumers incorporate extensive information into their expectations that originates outside the domestic economy. The demographics of an aging population has necessitated the shift from the acquisition of consumer durables and the accrual of debt toward the accumulation of assets and the preparation for retirement. Thus, the composition of cyclical changes in spending and saving behaviour are undergoing fundamental shifts. Research on how expectations should be measured involves both the question wording as well as the format in which the interviews are likely to take place. The evolving nature of the consumer therefore requires an updated methodology to yield these measures.

The differences that have been shown to exist between the US and UK indices may be sufficient to distinguish between the behaviour of the respective consumers. The implications thereof are likely to be evident in the underlying time series properties and in particular, the stationarity thereof. Easaw & Ghoshraya (2008) compare the symmetry of the oscillation between optimism and pessimism of the two countries, thereby indicating whether consumers' aspirations tend to persist optimistically or pessimistically. Persistent aspirations imply persistent consumption as it has been shown that sentiment predicts growth of household consumption in addition to income for both the US and UK. If sentiment evolves separately from the business cycle, the index would not reflect that of the business cycle and underlying economy. Asymmetry occurs if either troughs are more pronounced than peaks (this is referred to as deepness) or if contractions are steeper than expansions (this is steepness), in relation to the relative slopes of the series.

Easaw and Ghoshraya investigate the physical properties of the respective indices. Applying the Dickey–Fuller test which assumes a symmetric adjustment process to assess the order of integration, it was found that CS^{UK} is I(1), whilst CS^{UK} is I(0), as shown above. This test is misspecified if the underlying adjustment is asymmetric, and therefore a TAR (threshold autoregressive) model is applied to the respective indices. Under the TAR model [4] specification using a constant and a trend, both the CS^{US} and the CS^{UK} indices are non-stationary. The test was repeated by using only a drift term yielding the results qualifying the CS^{US} to be non-stationary. In the case of CS^{UK}, the null hypothesis was rejected at the 5% significance level indicating that the series is stationary. These results were consistent with the Dickey–Fuller tests.

[4]The Dickey–Fuller test for determining the order of integration of a time series process is of the following kind:

$$\Delta m_t \quad = \quad \gamma m_{t-1} + \epsilon_t,$$

where ϵ_t is a white noise error term. If ϵ_t is not white noise, an augmented Dickey–Fuller (ADF) test may be used where lagged values of Δm_t may be added to the right hand side. The null hypothesis ($H_0 : \gamma = 0$) is non-stationarity is tested against the alternative ($H_1 : -2 < \gamma < 0$) of stationarity. An alternative specification, the threshold autoregressive (TAR) model, is such that

$$\Delta m_t \quad = \quad I_t \gamma_1 (m_{t-1} - c) + (1 - I_t)\, \gamma_2 (m_{t-1} - c) + \omega_t,$$

where I_t is the Heaviside indicator function such that

$$I_t = \begin{cases} 1 & \text{if } m_{t-1} \geq c \\ 0 & \text{if } m_{t-1} < c. \end{cases}$$

This specification allows for asymmetric adjustment. If the system is convergent then the long-run equilibrium value of the sequence is given by $m_t = c$. The sufficient conditions for the stationarity of m_t are $-2 < \gamma_1 < 0$ and $-2 < \gamma_2 < 0$.

The CS^{UK} series exhibited no asymmetry (deepness) whilst the CS^{US} adjusted to the attractor asymmetrically; the series exhibited more momentum in the upward direction (when the series is increasing) than the downward direction. Both series, to a large extent, represent information contained in other current economic indicators. They also have the ability to forecast certain time series. There are some differences in this regard. From a statistical perspective, the time series differ in that the CS^{US} is I(1) and the CS^{UK} series is I(0).

The results show the differences in the underlying time series properties of the respective indices. The household aspirations for the UK exhibit reversion to a mean level whereas this adjustment does not occur in the case of the US. Asymmetric behaviour is identified in the case of US household aspirations which is contrary to the nature of economic cycles in which one expects contractions to be steeper than expansions. The empirical evidence suggests that expansions are steeper than contractions. They also find that the cyclical nature of household aspirations for both the US and UK is contrary to that of economic cycles, even if consumers account for prevailing economic conditions when forming their sentiments, which is a possibility according to Katona. This rationalises why sentiment is able to explain households' consumption behaviour (willingness), in addition to households' ability. The persistence of US household aspirations, which is contrary to prevailing economic conditions, suggests that consumers exhibit 'irrational exuberance'. Thus a spontaneous increase in household consumption would persist. Such asymmetry is not evident for the UK.

Sentiment cannot be ignored as a candidate leading indicator within the EWS framework of BL. The possibility of using such a measure, in addition to the imbalances that have been highlighted, may enhance the method of forecasting financial instability. Macro sentiment has been shown to contain information pertaining to various current and expected economic data. The relationships vary as sentiment causes and/or is caused by the variable in question. Consumer spending, a variable clearly associated with sentiment, constitutes a large proportion of total spending and is therefore a crucial determining factor of economic developments. On aggregate, the timing of decisions to purchase homes as well as incur debt influences the course of the entire economy. Large and infrequent spending and saving decisions are often associated with planning and deliberation rather than with impulse or habit. These decisions are not based solely on consumers' current economic situation, but also depend on their expectations about household income, employment, prices, and interest rates. Economic optimism and confidence exerts great influence on the course of the aggregate economy. The following sections examine the CS^{US} and CS^{UK} survey construction and time series properties. Macro sentiment and the aggregate stock market has been briefly mentioned in the introduction; further dissemination thereof with respect to each country will be explored in section 2.2.4.

2.2.1 The University of Michigan Consumer Sentiment Index

CS^{US} – Thomson, The University of Michigan Consumer Sentiment Index (not seasonally adjusted), Key Mnemonic UMCSENT – has proven to be an accurate indicator of the future course of the national economy. Consumers have the ability to predict interest rate changes, unemployment, changes in CPI, GDP and home sales; the predictive content of such surveys cannot be disregarded (Survey Research Center 2010). Fisher & Statman (2003) note that occasionally, the index diverges from such data and reacts to news of political content. They also find that consumers tend to be confident about the future when confident about the present. The CS^{US} is based on the following five questions: [5]

x_1 We are interested in how people are getting along financially these days. Would you say that you (and your family living there) are better off or worse off financially than you were a year ago?

x_2 Now looking ahead – do you think that a year from now you (and your family living there) will be better off financially, or worse off, or just about the same as now?

x_3 Now turning to business conditions in the country as a whole – do you think that during the next twelve months we'll have good times financially, or bad times, or what?

x_4 Looking ahead, which would you say is more likely – that in the country as a whole we'll have continuous good times during the next five years or so, or that we will have periods of widespread unemployment or depression, or what?

x_5 About the big things people buy for their homes – such as furniture, a refrigerator, stove, television, and things like that. Generally speaking, do you think now is a good or bad time for people to buy major household items?

[5] `http://www.sca.isr.umich.edu/documents.php?c=i`

The relative scores (the percentage giving favourable replies minus the percentage giving unfavourable replies, plus 100) for each of the five index questions is first computed. Each relative score is rounded to the nearest whole number. The formula shown below is applied to provide the CS^{US} – the five relative scores are added, divided by the 1966 base period total of 6.7558, and a constant 2.0 is added to correct for sample design changes from the 1950s: [6]

$$CS^{US} = \frac{\sum_{i=1}^{5} x_i}{6.7558} + 2.0.$$

Quarterly survey data for months 2, 5, 8, and 11 begin in November 1952; monthly data begins in January 1978. The results are released on the last business day at the end of every month. A preliminary result is released mid-month. To obtain monthly values for the initial quarterly series from January 1960 until December 1977, an interpolation in Eviews is performed. An alternative bimonthly index from the Conference Board is also available which has been published since 1967. Figure 2.1 graphically depicts sentiment – the index follows business cycle peaks and troughs, as dated by the National Bureau of Economic Research (NBER), and tends to follow a cyclical pattern, with a strong tendency to lead economic downturns and a lesser tendency to lead upturns. The series below is monthly and not seasonally adjusted, with the index first quarter 1966 = 100. Thus, the application of sentiment within the Index of Leading Economic Indicators renders the information content of the CS^{US} non-redundant.

Autocorrelation and partial autocorrelation for CS^{US} are in Figures 5.1 and 5.2 in the Appendix; the monthly data appear to be highly autocorrelated. This decays very slowly which is often the case with non-stationary time series. Partial autocorrelations assist in identification of the order of an autoregressive model; the partial autocorrelation of an AR(p) process is zero at lag p+1 and greater. If the sample autocorrelation plot indicates that an AR model may be appropriate,

[6] Another means to express this is as follows:

$$CS^{US} = \sum_{j=1}^{5} \left(P_{jt}^{f} - P_{jt}^{u} \right) 100 + 100,$$

where P_{jt}^{f} = the sample proportion giving favourable replies to the jth question at time t and P_{jt}^{u} = the sample proportion giving unfavourable replies to the jth question at time t. In terms of individual responses,

$$CS^{US} = \sum_{j=1}^{5} \sum_{i=1}^{n} \frac{x_{ijt}}{n} 100 + 100,$$

where $x_{ijt} = 1$ if favourable response to jth question by ith respondent at time t,n $x_{ijt} = –1$ if unfavourable response to jth question by ith respondent at time t and $x_{ijt} = 0$ for all other responses to jth question by ith respondent at time t.

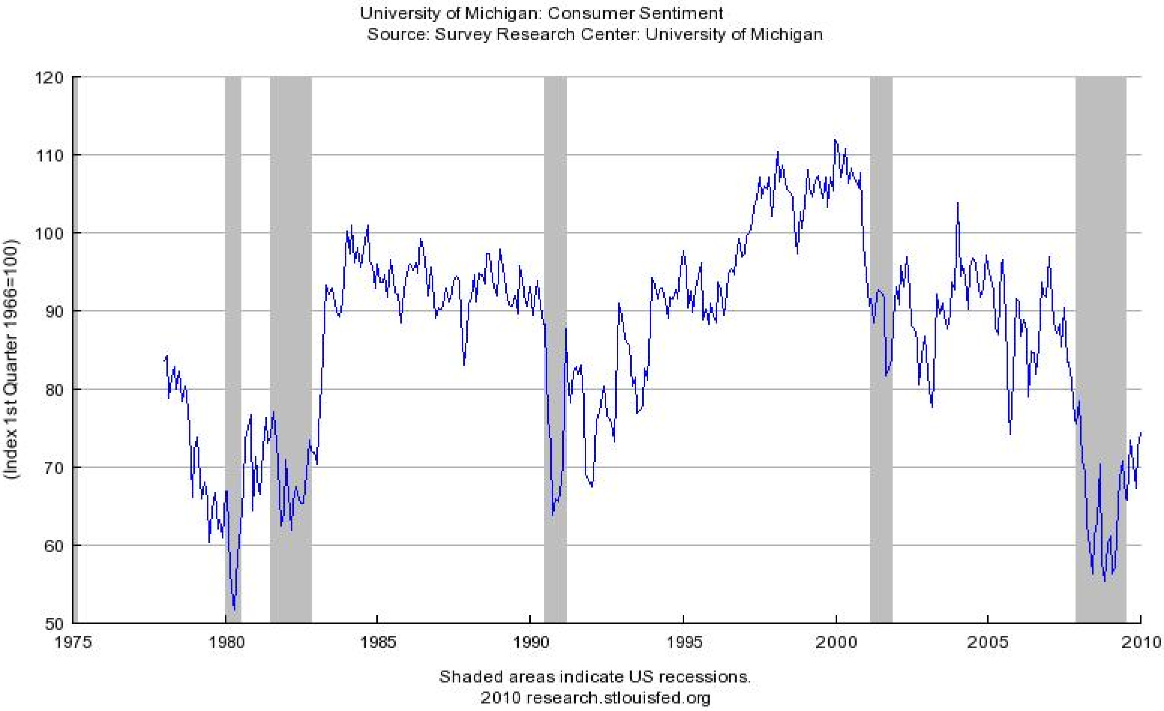

Figure 2.1: University of Michigan Consumer Sentiment Index. Source: Federal Reserve Bank of St Louis.

Table 2.2: Summary statistics for the (seasonally unadjusted) monthly CS^{US} for the period January 1960 to December 2008.

Summary statistics	CS^{US}
Mean	87.60
Median	90.9
Maximum	112
Minimum	51.7
Std. dev.	11.99
Skewness	–0.66
Kurtosis	2.89
Jarque–Bera	43.12
Probability	0

then the sample partial autocorrelation plot is examined to help identify the order. Within a 95% confidence interval, Figure 5.2 indicates that the CS^{US} monthly data is an AR(1) process. Data used are not-seasonally adjusted. Summary statistics for the period (588 observations) are in Table 2.2; the kurtosis here is not excess of the standard normal distribution of 3. If the kurtosis exceeds 3, the distribution is peaked (leptokurtic) relative to the normal; if the kurtosis is less than 3, the distribution is flat (platykurtic) relative to the normal.

Performing an ADF unit root test over the period, the null hypothesis cannot be rejected. The monthly CS^{US} has a unit root in the instance of constant, and constant with linear trend. The hypothesis of a unit root is accepted at the 1% confidence interval. The test statistic obtained $t_c = -3.04$ (p-value 0.03), and 1% critical value $t_{1\%} = -3.44$ for both intercept, and intercept and trend. This coincides with the result stated in Easaw & Ghoshraya (2008). Examining the first difference time series, the null hypothesis of the presence of a unit root is not accepted at the 1% significance level for both trend, and trend plus intercept; the test statistic of $t_c = -23.6$ is far less than both test critical values at all confidence levels. Thus the series is first difference stationary.

2.2.2 The GfK NOP Consumer Confidence Barometer

CS^{UK} – Thomson, UK GfK Consumer Confidence Barometer, not seasonally adjusted (NADJ), Key Mnemonic UKGFKCCNR – is the arithmetic average of the balances (in percentage points) of answers pertaining to the financial situation of households, the general economic situation, unemployment expectations (with inverted sign) and savings, all over the next 12 months. Balances provided for the European Commission (Thomson Key Mnemonic UKCNFCONQ) are seasonally adjusted (SADJ). The monthly question and answer selections are as follows:

- x_1 How has the financial situation of your household changed over the last 12 months? It has ... ++ 1 got a lot better, + 2 got a little better, = 3 stayed the same, – 4 got a little worse, – – 5 got a lot worse, N 9 don't know.
- x_2 How do you expect the financial position of your household to change over the next 12 months? It will ... ++ 1 get a lot better, + 2 get a little better, = 3 stay the same, – 4 get a little worse, – – 5 get a lot worse, N 9 don't know.
- x_3 How do you think the general economic situation in the country has changed over the past 12 months? It has ... ++ 1 got a lot better, + 2 got a little better, = 3 stayed the same, – 4 got a little worse, – – 5 got a lot worse, N 9 don't know.
- x_4 How do you expect the general economic situation in this country to develop over the next 12 months? It will ... ++ 1 get a lot better, + 2 get a little better, = 3 stay the same, – 4 get a little worse, – – 5 get a lot worse, N 9 don't know.

x_5 How do you think that consumer prices have developed over the last 12 months? They have ++ 1 risen a lot, + 2 risen moderately, = 3 risen slightly, – 4 stayed about the same, – – 5 fallen, N 9 don't know.

x_6 By comparison with the past 12 months, how do you expect that consumer prices will develop in the next 12 months? They will ++ 1 increase more rapidly, + 2 increase at the same rate, = 3 increase at a slower rate, – 4 stay about the same, – – 5 fall, N 9 don't know.

x_7 How do you expect the number of people unemployed in this country to change over the next 12 months? The number will ... ++ 1 increase sharply, + 2 increase slightly, = 3 remain the same, – 4 fall slightly, – – 5 fall sharply, N 9 don't know.

x_8 In view of the general economic situation, do you think now it is the right moment for people to make major purchases such as furniture, electrical/electronic devices, etc.? ++ 1 yes, it is the right moment now, = 2 it is neither the right moment nor the wrong moment, – – 3 no, it is not the right moment now, N 9 don't know.

x_9 Compared to the past 12 months, do you expect to spend more or less money on major purchases (furniture, electrical/electronic devices, etc.) over the next 12 months? I will spend ++ 1 much more, + 2 a little more, = 3 about the same, – 4 a little less, – – 5 much less, N 9 don't know.

x_{10} In view of the general economic situation, do you think that now is ...? ++ 1 a very good moment to save, + 2 a fairly good moment to save, – 3 not a good moment to save, – – 4 a very bad moment to save, N 9 don't know.

x_{11} Over the next 12 months, how likely is it that you save any money? ++ 1 very likely, + 2 fairly likely, – 3 not likely, – – 4 not at all likely, N 9 don't know.

x_{12} Which of these statements best describes the current financial situation of your household? ++ 1 we are saving a lot, + 2 we are saving a little, = 3 we are just managing to make ends meet on our income, – 4 we are having to draw on our savings, – – 5 we are running into debt, N 9 don't know.

Quarterly questions (January, April, July and October):

q_1 How likely are you to buy a car over the next 12 months? ++ 1 very likely, + 2 fairly likely, – 3 not likely, – – 4 not at all likely, N 9 don't know.

q_2 Are you planning to buy or build a home over the next 12 months (to live in yourself, for a member of your family, as a holiday home, to let etc.)? ++ 1 yes, definitely, + 2 possibly, – 3 probably not, – – 4 no, N 9 don't know.

q_3 How likely are you to spend any large sums of money on home improvements or renovations over the next 12 months? ++ 1 very likely, + 2 fairly likely, – 3 not likely, – – 4 not at all likely, N 9 don't know.

Results for CS^{UK} are available on the last working day of each month. Of note is that in the case of the CS^{US} index the first three and fifth questions are similar. The fourth question in the CS^{US} index asks what the consumer thinks will happen to the general economy during the next five years (instead of the next 12 months). Figure 2.2 displays the CS^{UK} and current seasonally adjusted GDP quarter-on-quarter (QoQ) percentage changes. The mid-1970 recession due to the oil crisis in 1973 is apparent. The 1974 Q1 growth of –2.5% was preceded by two successive period of negative growth followed by 1975 (Q2–Q3). Following this, recession dates include 1980–1981 (Q1–Q1), 1990–1991 (Q3–Q3) and 2008–2009 (Q1–Q3). Figure 2.3 displays the positive and negative QoQ GDP growth with CS^{UK} in order to observe this clearly.

Summary statistics for the SADJ and NADJ monthly time series for the period (420 observations) are in Table 2.3.

Table 2.3: Summary statistics for monthly CS^{UK} over the period January 1974 to December 2008.

Summary statistics	EU consumer confidence (SADJ)	GfK NOP (NADJ)
Mean	–9.1576	–7.1643
Median	–7.15	–7
Maximum	12	21
Minimum	–32	–39
Std. dev.	9.0549	10.3969
Skewness	–0.1995	–0.247
Kurtosis	2.3794	3.3775
Jarque–Bera	9.5252	6.7646
probability	0.0085	0.0340

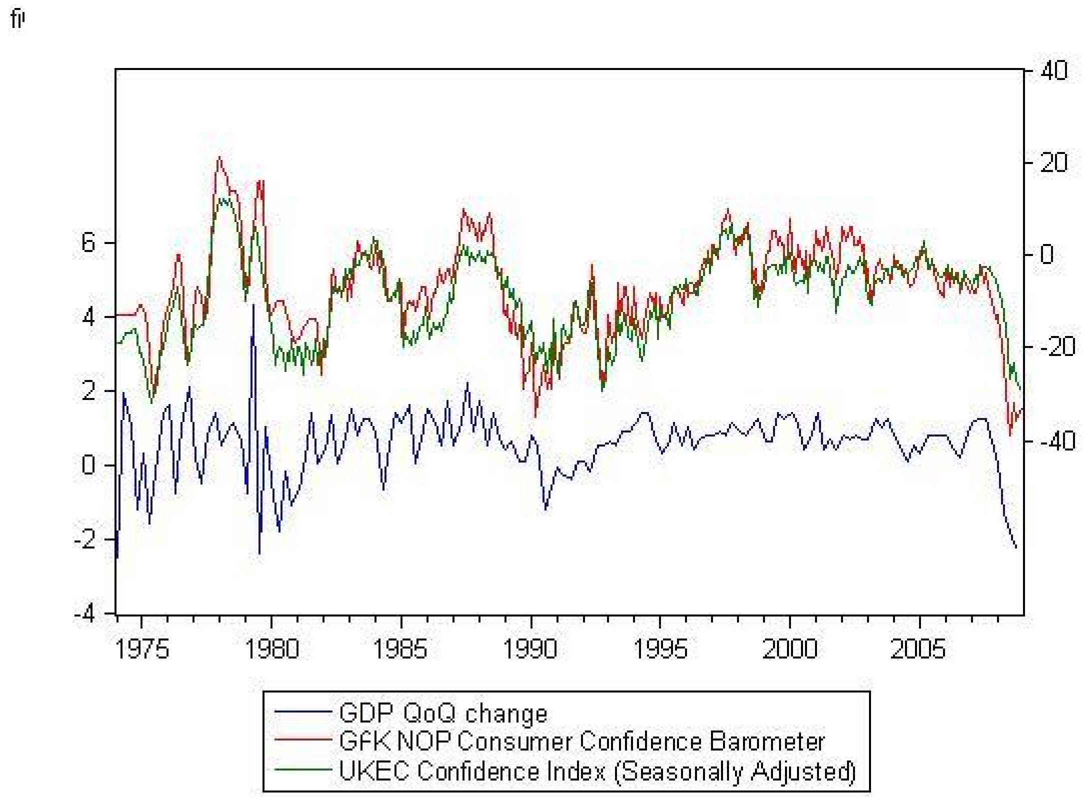

Figure 2.2: The quarterly SADJ (UKEC) and NADJ (GfK NOP) CS^{UK} for the UK with GDP QoQ % changes (seasonally adjusted).

In order to establish time series properties and compare this to the CS^{US}, the NADJ monthly time series will be used over the period January 1974 to December 2008. Performing an ADF test using a constant, the test statistic of $t_c = -3.27$ (p-value 0.02) is less than $t_{5\%} = -2.87$ at the 5% level. Thus the null hypothesis of the presence of a unit root is rejected. This is in agreement with Easaw & Ghoshraya (2008). In the instance a linear trend is included to the constant, the test is rejected at the 10% level. The critical value $t_c = -3.23$ (p-value 0.08) is less than $t_{10\%} = -3.13$. Applying a Dickey–Fuller test, the presence of a unit root is rejected at the 1% critical level with $t_{1\%} = -2.57$, $t_c = -3.01$. The Appendix contains the corresponding autocorrelation and partial autocorrelation in Figures 5.3 and 5.4.

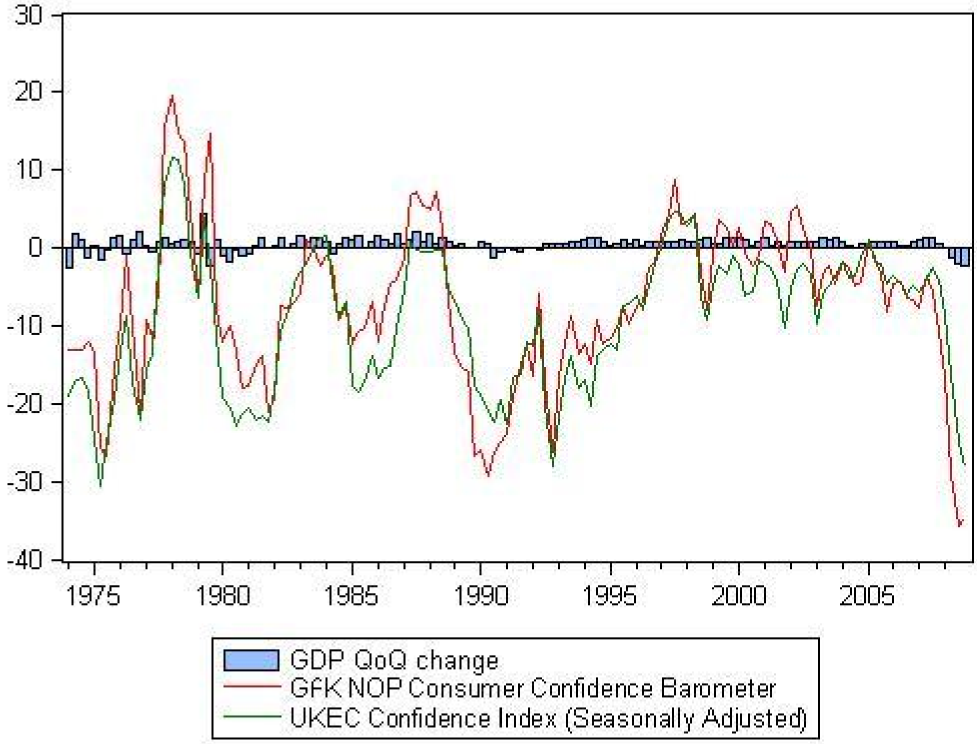

Figure 2.3: The quarterly SADJ UKEC) and NADJ (GfK NOP) CS^{UK} with GDP QoQ % changes (seasonally adjusted), alternative representation.

2.2.3 Macro Sentiment Trade Links

There are notable differences between the methodologies used to construct each country's macro sentiment index. The relationship between these measures may prove insightful, contingent on the dependencies that exist between the respective countries. Hence, establishing whether causality exists or whether CS^{US} can be used to forecast CS^{UK} might imply there are underlying relationships that deserve further investigation. Granger causality (including four lags) is then explored using the NADJ monthly indices between January 1974 and December 2008.

Granger-Causality using j lags are bivariate regressions of the form, and are evaluated for all pairs of series (x, y):

$$\begin{aligned} y_t &= \alpha_0 + \Sigma_{k=1}^{j} \alpha_k y_{t-k} + \Sigma_{i=1}^{j} \beta_i x_{t-i} + \epsilon_t, \\ x_t &= \alpha_0 + \Sigma_{k=1}^{j} \alpha_k x_{t-k} + \Sigma_{i=1}^{j} \beta_i y_{t-i} + \omega_t. \end{aligned}$$

The reported F-statistics are the Wald statistics for the joint hypothesis $\beta_1 = \beta_2 = \cdots = \beta_j = 0$ for each equation. The null hypothesis is that x does not Granger-cause y in the first regression and that y does not Granger-cause x in the second regression. Correlation does not imply causation; y is said to be Granger-caused by x if x helps in the prediction of y, or equivalently if the coefficients on the lagged x are statistically significant. Granger causality measures precedence and information content but does not imply causality in the more common use of the term. Although some results imply causality across asset class and fund group, in general it appears that performance Granger-causes flow. The two-way causality between institutional bond funds and performance is unique to the dataset yet 'performance Granger-causes flow' is stronger.

Results in Table 2.4 reveal that CS^{US} Granger-causes CS^{UK}. The ordinary (Pearson) correlation is 0.43 for this period.

Table 2.4: Granger causality for monthly CS^{UK} and CS^{US} over the period January 1974 to December 2008 using $j = 2$ lags. The null hypothesis is stated in column 1.

Null hypothesis	F-statistic	Prob.
CS^{UK} does not Granger cause CS^{US}	1.3446	0.2527
CS^{US} does not Granger cause CS^{UK}	3.4619	0.0085

Macro confidence is influenced by expected income and wealth; those assets which reflect a portion of that wealth are the aggregate financial market held by households, and residential real estate market. These values are determined by fundamentals, macroeconomic current and expected conditions and investor sentiment. High-frequency cross-border capital flows are likely to impact financial markets and allude to a means by which sentiment is propagated. Lower-frequency macro sentiment may diffuse across economies by alternative means. The real economy of a country that generates a large proportion of output from trade is likely to be subject to the influence of macro sentiment from its significant trade partners.

To determine whether this is feasible, the export–import bilateral trade relationship between the US and UK are explored with respect to macro sentiment. Monthly bilateral import and export trade data for both the US and UK is obtained from the IMF Direction of Trade Statistics (IMF DOTS) Database, World Bank (2011): World Development Indicators, ESDS International, University of Manchester. Lagged information pertaining to the strength of bilateral trade may be detected within macro sentiment. As a brief digression, the compelling question of whether macro sentiment is 'exported' is first examined.

Given that the difference between total exports and imports is included in the calculation of GDP, the significance of trade can be determined by the ratio of this difference to GDP, per quarter. The larger in absolute value this number is, the more significant trade becomes for that country. Bilateral trade strength is determined by the ratio of exports minus imports with respect to the trade partner, and GDP. In USD, one would expect these values to be equal in magnitude with opposite signs. However, inconsistencies between exports from the source country to the trade partner, and the partner's recorded imports from the source country are due to differences in classification concepts and detail, time of recording, valuation, and coverage, as well as processing errors. [7]

Let $e^j_{k,t}$ represent the value of exports to country k from country j (source country), and $i^j_{k,t}$ be the import value from country k to country j at time t, where $j = \{US,\ UK\}$, $k = \{US,\ UK\}$ and $j \neq k$. Total exports and imports of the source country j at time t are denoted by $\hat{e}^j_t$ and $\hat{i}^j_t$ respectively. Define total and bilateral trade strength at time t for country j with respect to country k as

$$T^j_{k,t} = x\frac{e^j_{k,t} - i^j_{k,t}}{GDP^j}, \tag{2.1}$$

$$T^j_t = x\frac{\hat{e}^j_t - \hat{i}^j_t}{GDP^j}, \tag{2.2}$$

where $x = \{3,\ 1\}$ if the period is monthly (average GDP in national currency) or quarterly respectively. The GDP of country j serves as the denominator as this is the reference variable that reflects current economic activity. Over the period of monthly data ($x = 3$) between 1974 and 2008, the relationship between macro sentiment, total trade strength and bilateral trade strength is examined. Figure 2.4 shows the monthly trade strength relationships as defined above. The right (left) hand axis refers to US (UK) trade strength. The more recent period, from January 1990 to December 2008. The UK is clearly negligible for the US as a trade partner. The US is importing more as a percentage of GDP over time. The UK appears to be exporting slightly more to the US, whilst total trade strength has decreased, thereby indicating a slight increase in exports as a percentage of GDP.

[7] `http://www.esds.ac.uk/international/support/user_guides/imf/dots.asp#fob`: 'Each individual country's export data is shown f.o.b. (free on board) whereas the import data is usually shown c.i.f. (cost, insurance, freight). UN guidelines recommend that imports be valued at the c.i.f. transaction value at the frontier of the importing country. For exports, the guidelines recommend valuation at the f.o.b. transaction value at the frontier of the exporting country.'

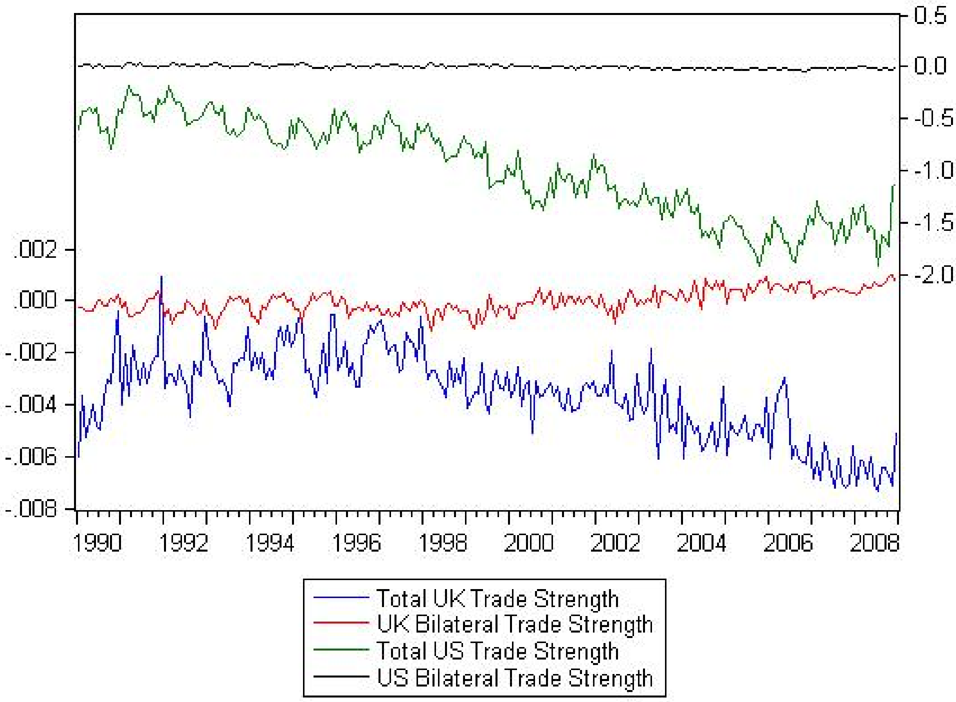

Figure 2.4: Monthly total and bilateral trade strength for both the US (right) and UK (left) from January 1990 to December 2008, calculated using equations (2.1) and (2.2).

Granger causality results using six lags are in Table 5.1 in the Appendix. Due to the lag effect of trade on an economy which is akin to lagged momentum, it is likely more useful to include a greater number of lags. Only those relationships which are significant and informative are reported. Results are for the entire period (January 1974 to December 2008) and for the more recent period (January 1990 to December 2008). Two-way Granger causality exists between the bilateral and total trade strength relationships in all possible combinations with the exception that T^{UK} did not Granger-cause T^{US} in either time period. The significance of trade variables running from the US to the UK appears to increase in the more recent period for all cases. The reverse occurs for the UK – the significance of UK bilateral trade for the US decreases. This is also the case with macro sentiment and bilateral trade strength: T^{US}_{UK} Granger-causes CS^{US}, however significance decreases. In general, trade strength Granger-causes macro sentiment; this may reflect the increased significance, reflected in macro sentiment, with which each country views economic-related data of the partner country, irrespective of bilateral trade strength. CS^{UK} Granger-causes T^{UK} in the more recent period. Correlations are in Table 5.2 in the Appendix for the latter period. CS^{UK} is slightly negatively correlated to all trade variables with the exception of T^{UK} and- T^{UK}_{US}.

These relationships alter over time due to globalisation, financial market integration and prevailing conditions with respect to both the monetary [8] and fiscal policy. Should trade reflect a small proportion of output, it then seems plausible that the effect of a diminished strength of trade will be less remarkable and therefore, macro sentiment of the source country may be affected proportionally over time. Thus, regardless of a country's status of being a significant trade partner (accountable for a large fraction of the exports from the source country), the effect of an adverse development in the trade relationship is likely to be relevant in the instance trade is significant to the source country, ceteris paribus. Thus, the ratio of total net trade to GDP is of relevance.

To conclude this section, results have shown that it may be the case that macro sentiment is 'exported' due to bilateral trade relations. The qualitative effect has not been fully established, however correlations do clarify synchronous effects. Within financial markets, high-frequency capital cross-border fund flows render themselves more suited as a measure of investor sentiment. This will be addressed in Chapter 4. The next section reviews literature which establishes the relationship between the aggregate equity market and macro sentiment.

2.2.4 Sentiment and the Aggregate Equity Market

Consumer sentiment has been used as a measure of investor sentiment as a means to forecast reversals in financial markets. These inefficiencies persist due to the limits of arbitrage. From a theoretical perspective, the behavioural model (De Long, Shleifer, Summers & Waldmann 1990) posits the existence of noise (irrational) traders which, due to 'correlated errors in beliefs', drives prices away from fundamentals for prolonged periods. Empirical validation of expected reversals based on the model requires a measure of sentiment which may be used to forecast or perceive market corrections. As financial market assets, and consequently personal wealth appreciates, consumers become more optimistic; so too do the prospects for the economy. Macro sentiment is therefore amenable to such research as it appears to incorporate the information of equity market movements as well as expected macro conditions.

[8] Currency fluctuations as a result thereof are not included in this research. The trade strength relationships for the UK are determined using IMF DOTS monthly trade data, IMF International Financial Statistics (IFS) Dataset to find the end-of-period GBP-to-USD conversion factor.

Otoo (1999) examines the effect of changes in equity prices on macro sentiment (University of Michigan and The Conference Board indices) in the US using monthly data from June 1980 to June 1999. Otoo examines whether sentiment increases due to the direct increase in wealth, or indirectly through the expectation of enhanced economic activity, and consequently labour income growth. Given that a more favourable current financial situation raises future sentiment levels, factors which may increase current or future wealth will likely increase sentiment. Therefore, positive changes in equity prices are likely to have a positive effect on sentiment. Greater wealth is also likely to lead to increased consumption. Results indicate that households use changes in stock prices as a leading indicator of future labour income; an increase in sentiment is positively contemporaneously related to an increase in stock prices, using the Wilshire 5000 as a measure for the aggregate market. Stock prices movements Granger-cause changes in sentiment, however the reverse relationship did not hold. Lagged sentiment did not affect stock prices. The direct effect of stock prices on the net worth of households was of less significance than the leading indicator effect.

Schmeling (2009) has examined the role of investor sentiment, proxied by consumer sentiment, in the aggregate stock market across 18 industrialised countries. His findings suggest that sentiment negatively forecasts aggregate stock market returns on average across countries. Periods of high investor optimism are followed by low stock market returns. Jansen & Nahuis (2003) examine aggregate financial market and confidence data for 11 countries (including the UK) over the period January 1986 to August 2001. The authors decompose the confidence indices into their components to establish whether the traditional wealth effect is significant, or whether an independent confidence channel exists. No long-run relationship between stock prices and sentiment was perceived. For the UK, they detect Granger causality running from the stock market to sentiment at both the one-month and the two-week lag – stock returns and changes in sentiment are positively correlated. They conclude that a stock market–confidence relationship exists due to macroeconomic expectations, as opposed to the wealth effect. Thus, the confidence channel is derived from the leading indicator property of stock prices.

Of relevance to financial instability are the extreme levels of exuberance perceived in markets. In these instances, excessive optimism might signal a reversal to be due based on the disconnection between market prices and fundamental values. With reference to the observed asset price inflation at that time, the phrase ‘irrational exuberance’ conveys the concern of the US Federal

Reserve Bank and the Chairman, Greenspan (1996):

> Clearly, sustained low inflation implies less uncertainty about the future, and lower risk premiums imply higher prices of stocks and other earning assets. We can see that in the inverse relationship exhibited by price/earnings ratios and the rate of inflation in the past. But how do we know when irrational exuberance has unduly escalated asset values, which then become subject to unexpected and prolonged contractions as they have in Japan over the past decade?

Hence, regardless of the prevailing low-inflation environment, prevailing asset valuations called into question the rationality of those driving prices. CS^{US} measured at 91.8 in December 1996; the index continued to steadily increase until January 2001, dropping off to 86.4. The recession of the early 2000s in the US has been dated by the NBER, [9] as lasting from March 2001 to November 2001. The NBER Business Cycle Dating Committee specified the peak in business activity to have occurred in March 2001. The peak of the business cycle expansion which had lasted 10 years was coincident to the onset of a recession. Confidence here had declined prior to this date. With respect to the aggregate market which is represented by the S&P 500 price index, Figure 2.5 graphically depicts the co-movements in the time series. Hence, macro confidence within the US both indirectly and directly appears to be related to the aggregate market.

The effect of macro sentiment cannot be ignored within the framework of Borio & Lowe (2002). Using this measure in addition to the domestic imbalances that have been highlighted may enhance the method of forecasting financial instability. The University of Michigan Consumer Sentiment Index and the GfK NOP Consumer Confidence Barometer will be used within the EWS framework to be described below.

2.3 Financial Instability – Banking Crises

Considering that this research is primarily concerned with the addition of macro sentiment into an existing EWS to detect impending crises, the motivation to substantiate the additional variable is based on the information content that cannot be gauged by examining other benchmark indicators. Macro sentiment in both the US and UK is a reflection of the expectations pertain-

[9] `http://www.nber.org/cycles.html`

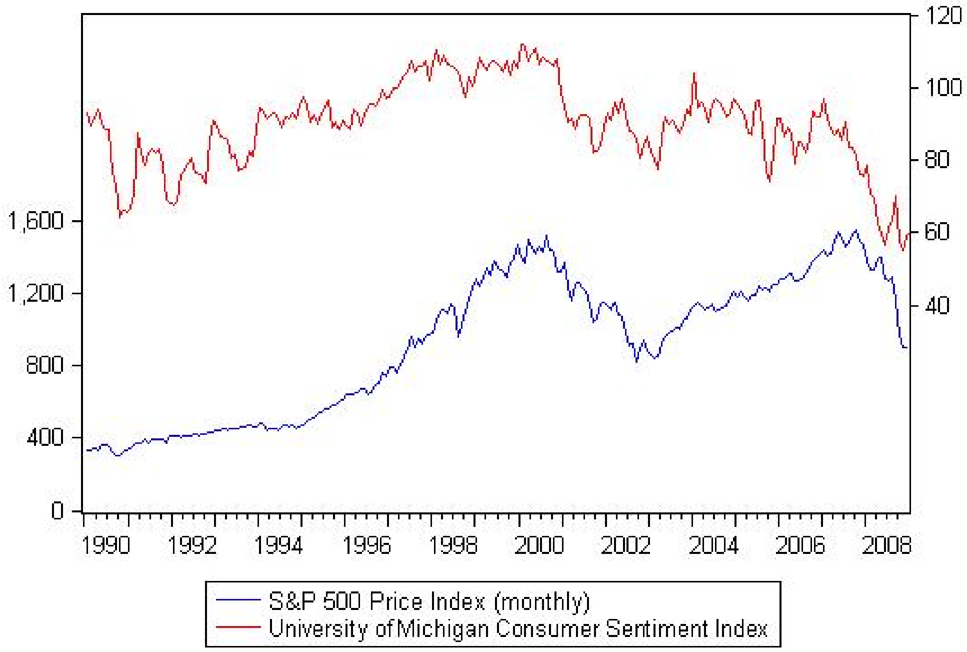

Figure 2.5: The monthly CS^{US} and S&P 500 price index series from January 1990 to December 2008.

ing to that economy and possibly, may be influenced by that emanating from closely associated countries, via strength of trade relations. Financial instability and macro prudential policy is both evolutionary and highly complex, as in some instances it involves the anticipation of aggregate behaviour that may arise due to the spread of fear or a shift in risk appetite, unrelated to fundamentals; thus macro sentiment may be instrumental to perceive these developments. In the context of the BL EWS, sentiment may address the inadequacies related to macro expectations.

Bell & Pain (2000) discuss the weakness of existing leading indicator models with regards to detecting banking crises. Individual bank failures, which may be due to microeconomic (bank specific) factors can take on systemic proportions, causing severe disruptions within the financial system. In the instance of market or credit risk exposure, an individual bank may be classified as technically insolvent if the value of liabilities exceeds that of assets. Information asymmetry between borrower and lender denies the ability to completely eliminate all related risks. However, the propensity to provide credit during market upswings naturally increases the risk associated with interest rate hikes as the difference in between asset and liability payments can lead to developments such as that of the Savings and Loans crisis in the US. Banks are also subject to liquidity risk – mass withdrawals are a result of a coordinated run on the bank.

Failure in the banking system may reflect a common fundamental weakness of individual banks or the susceptibility of all banks to a common shock. Thus systemic risk is closely related to financial contagion. Direct exposure between financial institutions is likely a transmission mechanism. Pure contagion, that which is independent of fundamentals, is also responsible for widespread bank runs. In this rare instance, Bell and Pain assert that the search for a leading indicator model may be futile. The application of a macro approach to identify system-wide vulnerability is not superfluous in general. The leading indicator approach of BL is an EWS which selects key variables to identify the associated imbalances within the banking system which therefore lead to financial instability.

2.3.1 The Borio–Lowe Early Warning System

BL assert that financial imbalances can be identified ex ante in what may appear to be 'benign financial conditions' due to low and stable inflation. Examining real asset prices (equity, commercial property and residential property) [10] from 1960 to 1999 in a range of developed and developing countries, [11] BL find that equity prices are the most volatile, followed by commercial property, and then residential property. Cycles occur in tandem with real economic activity and appear to be growing in amplitude and length. Peaks in equity prices tend to lead by one to two years those in the real estate market. Residential property prices are normally those that turn last. BL discern a relationship between large swings in asset prices and subsequent strains in the financial sector or the real economy which, in some cases, is accompanied by widespread financial distress. Laeven & Valencia (2008) find that a boom in real housing prices in the period preceding a crisis is followed by a decline, starting in the year of the crisis.

BL note that booms and busts in asset prices have tended to be a common feature of financial distress in both industrial and emerging economies. Examples in recent decades include Latin America in the late 1970s and early 1980s, the Nordic countries in the late 1980s, and East Asia in the mid- to late 1990s. Yet, the sparsity of datasets restricts incorporation into such

[10] BL include investment in their framework, however it did not prove to be useful and therefore is omitted here.

[11] Countries are limited to those that had a ratio of credit to GDP in excess of 35% any time between 1960 and 1999; had GDP per capita in 1995 in excess of US$ 4000 (at PPP exchange rates) and had total GDP in 1995 in excess of US$ 20 billion. Moreover, only countries with credit data and an equity price series since at least 1980 were considered.

studies. Thus, establishing a robust cross-country econometric link between asset price cycles and financial stability is not possible, and at best limited to equity prices. BL cite Kaminsky & Reinhart (1999) (KR) who find that equity prices decline in the nine months preceding a crisis and rise strongly in the nine months prior to that. BL state that '... it is unclear whether the fall in equity prices contributes to the crisis, or simply reflects the market's expectation that a crisis is more likely'. This statement essentially impels the use of macro sentiment as a means to account for expectations. Limitations naturally arise due to data availability. Yet, in order to assess whether it may be feasible, the use thereof in markets where it has a long-standing and stable history may generate discussion regarding future incorporation into an EWS framework.

Henceforth, the aggregate equity market for the US refers to the S&P 500 price index as it is regarded as the best single gauge of the large-cap US equities market. It includes 500 leading companies in leading industries of the US economy, capturing 75% coverage of US equities. For the UK, equity prices refer to the FTSE All-Share Index which represents 98–99% of UK market capitalisation and is an aggregation of the FTSE 100, FTSE 250 and FTSE Small Cap Indices. Residential property is included using the US S&P/Case–Shiller house price index and the UK Nationwide house price index.

BL cite domestic credit growth as a factor (imbalance) which increases the risk of financial instability (systemic banking crises). Bell & Pain (2000) find that property-related lending is associated with an increased risk of failure. BL emphasise the interactions between asset and credit imbalances which pose a threat to the stability of the financial system. Thus, 'it is the simultaneous occurrence of rapid credit growth, rapid increases in asset prices and, in some cases, high levels of investment - rather than any one of these alone - that increases the likelihood of problems'.

Their approach builds on the work of KR in which a threshold value for each of the relevant indicator series is identified through an optimisation search programme. If the indicator value exceeds that of the threshold value, this is classed as a 'boom' which may signal an impending crisis. The approach of BL differs as they focus on cumulative processes rather than growth rates over just one year. This is enforced by the use of the one-sided Hodrick–Prescott (HP) filter, addressed below. BL also limit the analysis to banking crises, and therefore to a few significant indicators. The following definitions are relevant in the empirical analysis.

Definition 2.2 *A credit boom is a period in which the ratio of private credit to GDP deviates from its trend by an identified threshold value. The deviation is termed the credit gap.*

A gap may develop either through excessive growth over one year or as the result of a number of years of above-trend growth. Credit is specific to claims on the private sector of the domestic economy. The private credit-to-GDP ratio gauges the relative size of credit in the economy. By dividing credit by GDP in nominal terms, price effects are expunged.

Definition 2.3 *An asset price boom is a period in which real asset prices, nominal prices deflated by the consumer price index (CPI), deviate from their trends by an identified threshold value. This deviation is the asset price gap.*

The gaps are the indicator values which are used to determine whether a boom exists. The threshold value for the credit gap is defined in terms of the deviation in percentage points of the actual credit ratio from the trend ratio. For the asset price gap, the threshold value is expressed as the percentage deviation from the trend. This is a non-parametric approach which assesses the behaviour of single variables prior to and during crisis episodes. If unusual behaviour of a variable can be quantitatively identified and thereby defined based on past tranquil market conditions, then that deviation forewarns against an impending period of instability. This is then identified as an imbalance of the relevant series.

Formally, let i reflect the indicator time series which pertains to real assets, credit or macro sentiment; $j = \{US,\ UK\}$ refers to the country; X denotes a binary signal. It follows that the ith indicator variable which pertains to country j at time t is denoted by i_t^j. The associated trend, gap and threshold values are denoted $\hat{i}_t^j$, $\hat{i}_{g,t}^j$ and $\hat{i}_T^j$. The signal which relates to indicator i and country j is X_i^j . Thus, $X_i^j = \{0,\ 1\}$, contingent on whether the indicator exceeds the threshold value. A signal is 'on' if $X_i^j = 1$. Thus,

$$X_i^j \quad = \quad \begin{cases} 1 & \text{if } |i_t^j| > |\hat{i}_T^j| \\ 0 & \text{otherwise.} \end{cases}$$

According to Definitions 2.2 and 2.3, the following notation will be used to estimate i_t^j at time t, where i refers to one of the following indicator series. The aggregate equity index is denoted S_t, and associated returns for the preceding period (quarterly or annual) R_t:

$$p_t^j = \frac{\text{Private Credit}_t^j}{\text{GDP}_t^j}, \tag{2.3}$$

$$e_t^j = \frac{S_t^j}{\text{CPI}_t^j}, \tag{2.4}$$

$$h_t^j = \frac{\text{HPI}_t^j}{\text{CPI}_t^j}, \tag{2.5}$$

$$c_t^j = CS_t^j. \tag{2.6}$$

Consequently, associated trends are $\hat{p}_t^j$, $\hat{e}_t^j$, $\hat{h}_t^j$ and $\hat{c}_t^j$ respectively. The gaps are determined from these values:

$$p_{g,t}^j = p_t^j - \hat{p}_t^j, \tag{2.7}$$

$$e_{g,t}^j = \frac{e_t^j - \hat{e}_t^j}{\hat{e}_t^j}, \tag{2.8}$$

$$h_{g,t}^j = \frac{h_t^j - \hat{h}_t^j}{\hat{h}_t^j}, \tag{2.9}$$

$$c_{g,t}^j = \frac{c_t^j - \hat{c}_t^j}{\hat{c}_t^j}. \tag{2.10}$$

The concept of an imbalance is not necessarily relevant to sentiment, however the deviations from trend can be interpreted as either extreme optimism (pessimism) in the instance the gap is positive (negative). Only ex ante information is required in determining whether a boom exists. Accordingly, a rolling one-sided HP filter is applied to the individual series to estimate the gaps: The threshold values that define the existence of a boom can be determined without reference to the entire history of the relevant series. This also has the effect of accounting for the cumulative process, not just the growth rate over a specified period. The first 10 years of data are used to find an initial trend. A lead of two years is applied in the instance of the real equity price gap: at time t, to ascertain whether the equity price gap exceeds a particular threshold, the level of the equity price gap two years earlier is used. The condition at time t checks $|e_{g,t-2}^j| > |e_T^j|$. Equity markets are considered to be a fairly accurate leading indicator of economic activity and financial instability, with the lead being one to two years. Additionally, often a boom in equity precedes one in property markets with a lead of roughly two years. Thus, in the absence of data on property prices, BL introduced this convention.

BL consider combinations of indicators, rather than individual thresholds which may provide the most useful signals. As it is extremely precarious to predict the exact timing of a crisis despite the certainty of it, the search is conducted over multiple horizons of one to three years. An indicator is judged to successfully signal a crisis if it switches to being 'on' either prior to, or in the year of the crisis. BL use crisis dating from Bordo, Eichengreen, Klingebiel, Martinez-Peria & Rose (2001). A similar optimisation procedure to that of KR[12] is employed over the dataset. BL find that the best combination appears to be for a credit gap of 4%, and an asset price gap of 40%.

The methodology outlined above is adhered to as closely as possible, limiting the analysis to the US and the UK. Data examined is both annual and quarterly from 1960 until 2008 for the US and from 1974 to 2008 for the UK, to be discussed in section 3.5.1. Data 10 years prior to the starting dates are used to obtain the initial trend. Prior to this period, it is either unavailable or patchy. The definition and classification of banking crises have been derived from historical episodes. Indicators thereof vary considerably across the related literature in the attempt to identify crisis start and end dates and the severity of the crisis. Government intervention and broad responses of institutions are crucial in the identification process using information gleaned from bank regulators and/or central banks. Boyd, De Nicolò & Loukoianova (2009) conclude that 'In virtually all cases, what is measured is, effectively, a government response to a perceived crisis – not the onset or duration of an adverse shock to the banking industry'. Thus, there is a discrepancy about crisis dating, duration and whether it may be considered systemic or not. They amalgamate banking crisis-related data from four of the main sources: Laeven & Valencia (2008), Caprio & Klingebiel (1999), [13] Demirgüç-Kunt & Detragiache (2005) and Reinhart & Rogoff (2008). Due to the inability to find a common source agreeing about specific dates and duration, the focus will be on the year in which the banking crises have been dated in Laeven & Valencia (2008). According to this source, a Type I crisis is systemic and Type II is a case of financial distress. The following section reviews the HP filter and the application to detrending

[12] This involves minimising the noise-to-signal ratio: The noise-to-signal ratio is defined as the ratio of the size of Type II errors (the percentage of non-crisis periods in which a crisis is incorrectly signalled – a false alarm) to one minus the size of Type I errors (the percentage of crises that are not correctly predicted). When searching for the optimal threshold values, the noise to signal ratio should be minimised to ensure the number of crisis correctly predicted is optimal. A Type I error occurs when the null hypothesis is mistakenly rejected and a Type II error occurs when the null hypothesis is mistakenly accepted.

[13] `http://www1.worldbank.org/finance/html/database_sfd.html`

time series data.

2.3.2 The Hodrick–Prescott Filter

Hodrick & Prescott (1997) [14] propose a linear filter to decompose non-stationary macroeconomic time series into a stationary business cycle component and a non-stationary trend component which is the long-run path. Macroeconomic time series often have an upward drift or trend which renders them non-stationary. Since many statistical procedures assume stationarity, it is often necessary to transform data prior to analysis; a number of familiar transformations include deterministic detrending, stochastic detrending and differencing. The HP filter is a two-sided symmetric moving average filter and has been shown to transform series which are integrated of order 4 I(4) or less into stationary series. It is assumed that the data are seasonally adjusted. [15] Prior knowledge is that the growth component varies 'smoothly' over time.

A time series y_t is then the sum of a non-stationary trend component g_t, and a cyclical stationary component c_t:

$$y_t = g_t + c_t$$

for $t = 1, 2, \ldots, T$. The measure of the smoothness of the $\{g_t\}_{t=1}^{t=T}$ path is the sum of the squares of its second difference. The c_t are deviations from g_t; over long time periods, their average is near zero. Thus, the following programming problem determines the growth components:

$$\min_{g_t} \left\{ \sum_{t=1}^{T} (y_t - g_t)^2 + \lambda \sum_{t=2}^{T-1} \left[(g_{t+1} - g_t) - (g_t - g_{t-1})\right]^2 \right\}$$

for $t = 1, 2, \ldots, T$. The first term is the goodness of fit whilst the second term is the penalty for roughness. λ is a smoothing parameter: as $\lambda \to 0$, the trend approximates the actual series and as $\lambda \to \infty$, the trend becomes linear. The values for this parameter are the subject of much debate, with the standard value of 100 for annual data, 1600 for quarterly data and 14 400 for monthly data. The authors find that if c_t and the second difference of g_t, $\Delta^2 g_t$, are identically and independently distributed (iid) normal random variables with mean zero and variances σ_c^2 and $\sigma_{\Delta^2 g}^2$ respectively then the best choice is $\lambda = \sigma_c^2 / \sigma_{\Delta^2 g}^2$. As in the case of GDP in which

[14] The original article was printed in 1981 as a Working Paper, by Carnegie-Mellon University.

[15] BL did not adjust the data for seasonality to allow for the accumulation of imbalances.

the natural logarithm is applied to the series and trend, λ can be interpreted as a penalty on movements in the growth rate of the trend component.

The method proposed in Borio & Lowe (2002) is the use of a rolling one-sided HP filter; as new data become available, the HP filter is applied to the entire series with the final time T trend value being used for that end point T. This is in contrast to the standard application whereby one applies the HP filter to the entire time series. In doing so, all data at any time $t < T$, rather than using currently available information, are required. Another slight modification is the use of $\lambda = 1600$ for annual data. This has the effect of accounting for the accumulation of imbalances.

Kydland & Prescott (1990) discuss the purely statistical decomposition into trend and cycle with respect to real business cycle theory. The trend should be a linear transformation of a time series; lengthening the time series should not alter the deviations too much (apart from towards the end). The use of the HP filter is applied to the natural logarithm of GNP data ensuring that the data are positive. They find that the filter leads to spurious cycles and/or distorts unrestricted estimates of the cyclical component. Thus, Kydland and Prescott recommend using a framework which presents the stylised facts associated with trend and cycle, and which fits both components at the same time.

Harvey & Jaeger (1993) also show that the uncritical use of mechanical detrending can lead to spurious cyclical behaviour. Structural time series models provide a better means to report stylised facts of such data. The HP filter fits a smooth curve through a set of points and is equivalent to a structural time series model, imposing certain restrictions. Applying the HP filter to the quarterly real natural logarithm of US GNP data, they find that it is equivalent to estimating the structural time series model. The coincidence between the estimated business cycle component and the HP estimated cycle suggests that the HP filter is tailor-made for extracting the business cycle component from US GNP. However, this is certainly not always the case for all macroeconomic time series.

Cogley & Nason (1995) distinguish the HP filter's effects on trend- and difference-stationary time series (TS and DS, respectively). Previous results rely on theorems which assume that the original data are stationary. When applied to stationary data, the filter operates like a high-pass filter, damping fluctuations which last longer than eight years per cycle (in quarterly data) and passing shorter cycles without change. The filter is typically applied to non-stationary data. In the case of TS data, HP filtering is conceptually equivalent to a two-step operation: linearly detrend the data and then apply the HP filter to deviations from trend. Thus the HP filter operates like a high-pass filter on deviations from trend. When the data are DS, the HP filter is equivalent to a two-step linear filter: difference the data to induce stationary, then smooth the differenced data with an asymmetric moving-average filter. The smoothing operation amplifies growth cycles at business cycle frequencies and damps long- and short-run fluctuations. As a consequence, the filter can generate business cycle periodicity and comovement even if none are present in the original data. In this respect, applying the HP filter to an integrated process is similar to detrending a random walk. Cogley and Nason state that since the filter can generate spurious cycles when applied to integrated processes, it is not clear whether the results should be interpreted as facts or artifacts. They conclude that if the data are assumed to be DS, stylised facts about periodicity and comovement primarily reflect the properties of the filter and very little about the dynamic properties of the underlying data.

Ravn & Uhlig (1997) study how one should adjust the filter according to the frequency of data. They survey literature which has argued that the filter might lead to spurious cycles if the data is DS. Further to this, the filter is only optimal (in the sense of minimising the mean square error) in a certain instance and may produce extreme second-order properties in the detrended data. Ravn and Uhlig conclude that none of the detected short-comings or undesirable properties are particularly compelling. Thus, the HP filter will remain the standard method for detrending time series.

The literature which surveys the use of the HP filter is extensive, particularly in the application to detrend GDP data. Use is often cautioned, however it remains one of the most distinguished methods.

2.4 Empirical Section

2.4.1 Data

US data span the period from 1960 to 2008; UK data are examined from 1974 to 2008. Macro sentiment data has been described in sections 2.2.1 and 2.2.2. Both annual and quarterly data will be employed, however sentiment will only be examined in the latter instance. Having clarified the exact data series used in the reference paper, [16] the following time series are obtained for the US in Table 2.5 and the UK in Table 2.6. The property price index as well as macro sentiment are novel to the EWS. No seasonality adjustments are performed, in line with the original work; some data has been seasonally adjusted by the IMF International Financial Statistics (IMF IFS) prior to publication. [17] Private credit may represent slightly different groups for the US and UK as the data sources vary. Consistency has been maintained according to BIS sources.

Table 2.5: Data for the US to be examined from January 1960 to December 2008. Both source and data series are provided. These data are quarterly frequency.

US data		
Variable	Source	Series
Private credit – the sum of:		
Nonfinancial business credit market instruments, excluding corporate equities liability;	Federal Reserve Board	Z1/Z1/FL144104005.Q
Households and nonprofit organisations credit and equity market instruments liability	Federal Reserve Board	Z1/Z1/FL154102005.Q
Seasonally adjusted GDP	IMF IFS	99B.CZF GDP billions USD
CPI [1]	IMF IFS	64...ZF CPI Index
S&P500 composite index	Thomson Datastream	S&PCOMP
Case–Shiller national HPI (1987–2008)	Thomson Datastream	USCSHP...F
Nominal HPI (1960–1987)	Robert J. Shiller [2]	PHCPI

[1] CPI = 100 in the year 2005.
[2] www.irrationalexuberance.com/Fig2.1Shiller.xls

2.4.2 US Crisis Prediction

The US suffered from two systemic banking crises during the selected period:

1. 1988 – Savings and Loans (S&L) crisis. This resulted in the failure of over 1400 savings and

[16] Jakub Demski, Statistical Analyst, Monetary and Economic Department at the Bank for International Settlements (Jakub.Demski@bis.org).
[17] http://www.esds.ac.uk/international/support/user_guides/imf/Introduction.pdf

Table 2.6: Data for the UK to be examined from January 1974 to December 2008. Source and series is provided; quarterly frequency is applied.

UK data		
Variable	Source	Series
Claims on private sector	IMF IFS	32D...ZF billions GBP
Seasonally adjusted GDP	IMF IFS	99B.CZF billions GBP millions GDP
CPI	IMF IFS	64...ZF CPI Index
FTSE All Share Price Index	Datastream	FTALLSH
Nominal HPI (1973–2008)	Nationwide	HPI

loan institutions and over 1300 banks; the estimated cost is 3% of GDP. These bailouts can be incomplete or misspecified as the fiscal costs cannot always be accurately apprehended. The share of non-performing loans at peak was 4.1%. Bell & Pain (2000) attribute the crisis to the inability to determine or hedge against interest rate risk as the S&L institutions had substantial fixed-interest assets when market interest rates, and consequently their funding costs, rose sharply.

2. 2007 – Subprime mortgage crisis. This crisis was initially manifest in liquidity difficulties within the banking system as demands for asset-backed securities declined. Those hard-to-value derivatives which were sought after during the boom were marked down dramatically. Credit losses and writedowns worsened as mortgage foreclosures increased in 2006, 2007 and 2008. By June 2008, subprime-related and other credit losses by global institutions were roughly $400 billion. Although not addressed here, direct transmission occurred through ownership of mortgage debt.

Both p_t^{US} and $\hat{p}_t^{US}$, as well as annual real credit growth, are displayed in Figure 2.6 for the United States from 1960 to 2008. Real annual credit growth[18] peaked in 1984 at 10.8% followed by 10.1% in 1973, 8.5% in 1965 and 8.1% in 1999. Three noticeable minima occurred: –4.2% in 1975, –3.9% in 1991 and –3.1% in 1982. These correspond to business cycle troughs as dated according to the NBER. The recession from November 1973 to March 1975 was marked by the 1973 oil crisis and

[18]Credit was converted to a real value using the CPI (base year = 2005).

the 1973–1974 stock market crash. The period is remarkable for rising unemployment coinciding with rising inflation (stagflation). The recession from July 1981 to November 1982 has been attributed to tight monetary policy required to control inflation, resulting from the associated energy crisis in 1979 (Iranian revolution). The recession from July 1990 to March 1991 was a combination of weakened growth due to interest rate hikes between 1986 and 1989 required to curb inflation, the 1990 oil shock, debt accumulation of the 1980s, and new banking regulations following the S&L crisis. Consumer pessimism has also been cited as one of the determining factors. Peaks in the credit gap occurred in years $t = 1974$, $p_{g,t}^{US} = 5\%$, $t = 1987$ $p_{g,t}^{US} = 13\%$ and $t = 2007$, $p_{g,t}^{US} = 17\%$.

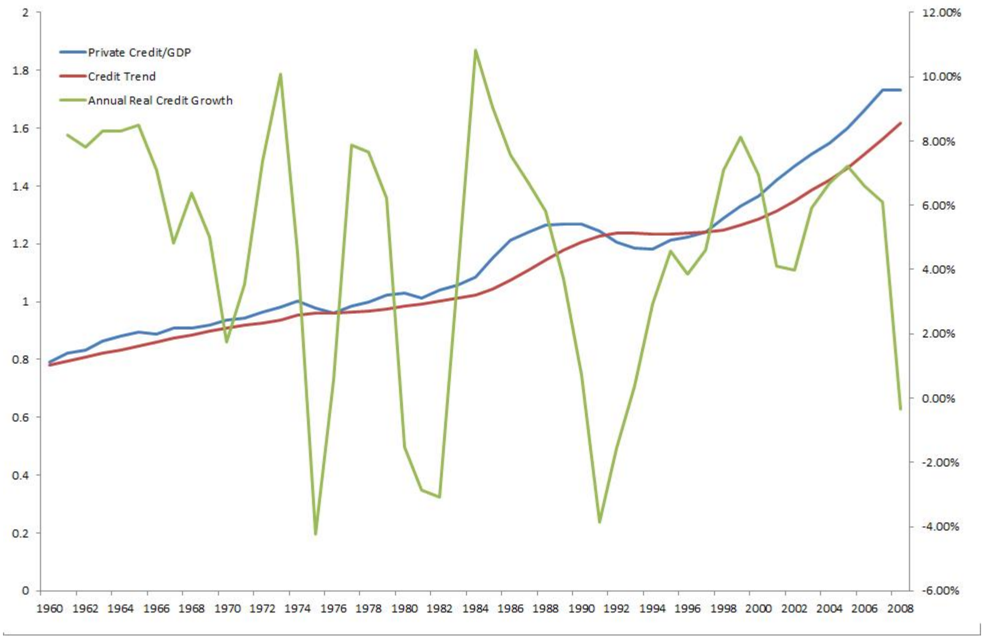

Figure 2.6: The series p_t^{US}, $\hat{p}_t^{US}$ (left axis) and real annual credit growth (right axis). This graph depicts the fluctuations in real annual credit growth relative to the private credit-to-GDP p_t^{US} and the associated trend $\hat{p}_t^{US}$ thereof.

The h_t^{US} and $\hat{h}_t^{US}$ indicate that steady growth followed by rapid increases in real house prices started from 2000 onwards, as shown in Figure 2.7. There are three noticeable maxima displayed: 1979, 1989 and 2006. Thus, using h_t^{US} as an indicator appears to be beneficial as $h_{g,t}^{US} > 0$ prior to both the S&L and subprime 2007 crisis. Figure 2.8 displays the annual $p_{g,t}^{US}$, $e_{g,t}^{US}$ and $h_{g,t}^{US}$.

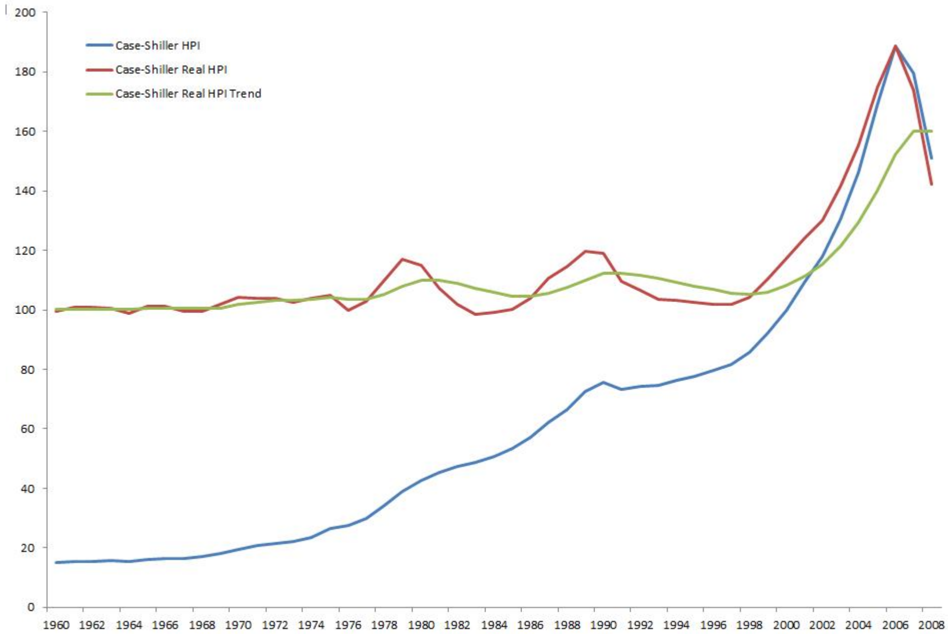

Figure 2.7: The real HPI h_t^{US} and real HPI trend $\hat{h}_t^{US}$ for the US calculated using the Case-Shiller HPI and the CPI over the selected period.

In Table 2.7, the gaps are provided five years prior to and for the year corresponding to identified crises; $e_{g,t}^{US}$ refers to current data and does not reference e_{t-2}^{US} as property prices are available too. The $p_{g,t}^{US}$ is the most reliable indicator. The $h_{g,t}^{US}$ is a more reliable indicator for the subprime crisis than the S&L crisis. The movements in $e_{g,t}^{US}$ are opposed to those of the $h_{g,t}^{US}$. The annual simple returns are included as a comparison. Evidently, equity market appreciation requires a number of years to accumulate gains after a decline in trend following multiple years of negative returns. Therefore, even though 2003 produced a large annual return, the previous crash and subsequent negative returns resulted in a negative gap.

Quarterly results are in Table 5.2 in the Appendix which includes macro sentiment indicator c_t^{US}. In this instance, the HP filter is applied with smoothing parameter $\lambda = 14\,400$ to capture the cumulative process. The first 40 observations (10 years) are used to find the initial trend. The results display a similar pattern, however data frequency clearly affects gaps. The $p_{g,t}^{US}$ is slightly positive prior to both episodes. BL assert a threshold value of 4% indicates impending instability – this is in 1986Q4 prior to the S&L crisis and remained below this prior to the subprime crisis. For real asset price gaps, 40% was the suggested threshold value. In the results here, $e_{g,t}^{US}$ remains below 20% prior to both crises, however does tend to peak in the years preceding the events. The $h_{g,t}^{US}$ is smaller than $e_{g,t}^{US}$ in general. In the case of the subprime crisis, the gap peaks two years

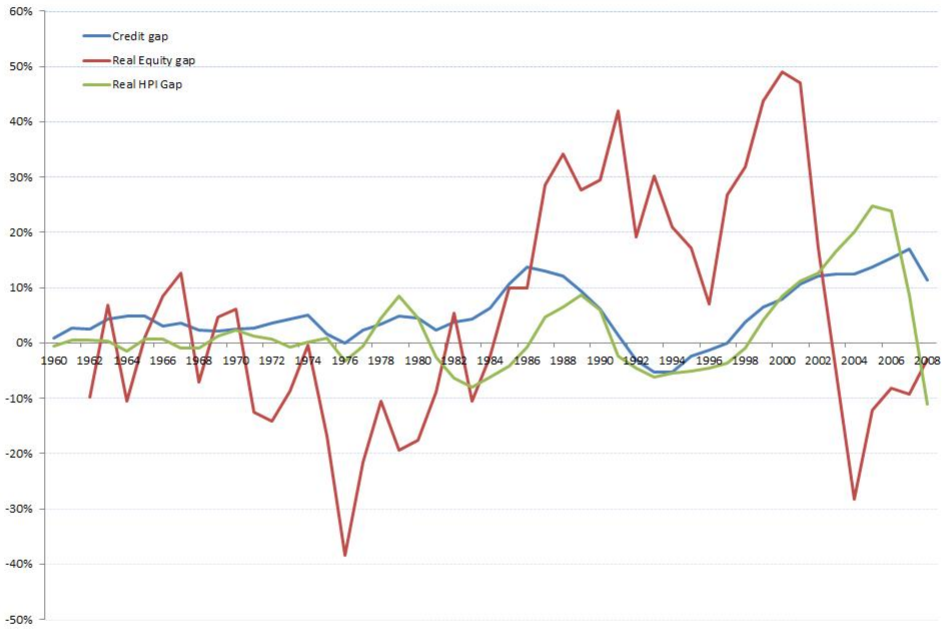

Figure 2.8: The annual gaps corresponding to credit, equity and house prices as given by $p_{g,t}^{US}$, $e_{g,t}^{US}$ and $h_{g,t}^{US}$.

Table 2.7: Indicator gaps and nominal annual equity returns R_t five years prior to and during the year of the crises within the US. No decimals are omitted.

Year	$p_{g,t}^{US}$	$e_{g,t}^{US}$	$h_{g,t}^{US}$	R_t
1983	4%	10%	–8%	10%
1984	6%	10%	–6%	–2%
1985	11%	29%	–4%	19%
1986	14%	34%	–1%	10%
1987	13%	28%	5%	0%
1988	12%	29%	7%	8%
2002	12%	–28%	13%	–29%
2003	12%	–12%	17%	22%
2004	13%	–8%	20%	6%
2005	14%	–9%	25%	0%
2006	15%	–3%	24%	9%
2007	17%	–5%	9%	0%

prior to the crisis. Quarterly data have a slightly different result to annual results and are likely more useful. Figure 2.9 displays the quarterly time series of c_t^{US}, e_t^{US} and h_t^{US}. Macro sentiment appears not to have increased markedly in response to the house price index. Given that residential property is a substantial portion of wealth for many consumers, the positive effect of such an increase does not seem to filter through to the sentiment measure. Thus, it may be that equity markets have a psychologically greater effect on future expected wealth than an appreciation of property.

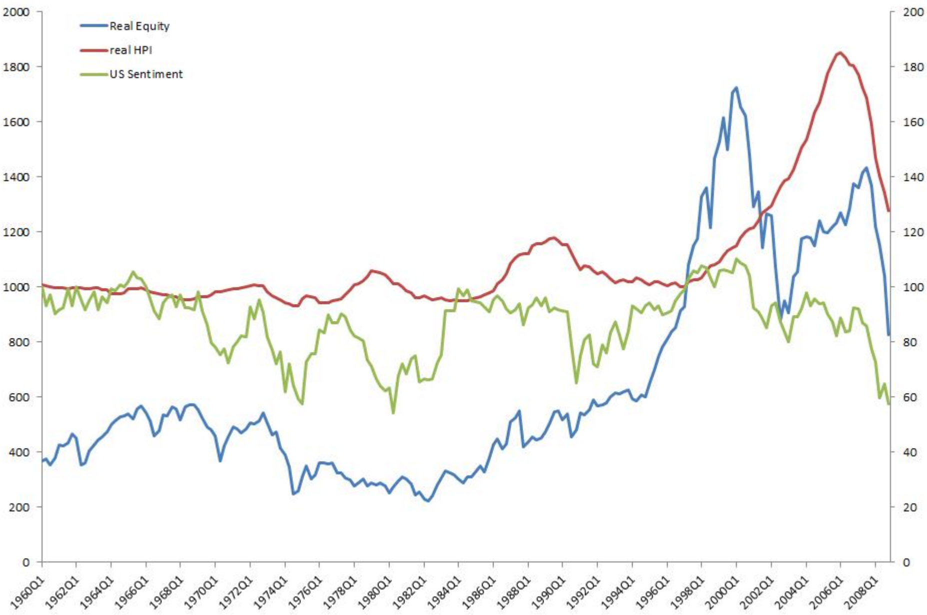

Figure 2.9: Quarterly data pertaining to equity, house prices and consumer sentiment given by e_t^{US} (left axis), h_t^{US} and c_t^{US} (right axis), respectively.

All quarterly gaps are shown in Figure 2.10. Up until the early 1980s, $e_{g,t}^{US}$ and $c_{g,t}^{US}$ seem to move in lock-step. Thereafter, the gaps are divergent until the early 2000s. Empirical results have suggested that contemporaneous aggregate equity market returns and changes in sentiment are positively correlated and statistically significant. However, different time periods suggest different factors possibly taking precedence. Macro sentiment appears to reflect different factors at different times, contingent upon macroeconomic conditions. With respect to the 1988 crisis, $c_{g,t}^{US}$ declined from 1986Q2, becoming negative in 1985Q1; a minimum of –10% in 1987Q4 is recorded. In the second crisis, the $c_{g,t}^{US} < 0$ in the second half of 2005, and in the second and third quarter of 2006.

Examining the gaps over the period, the following notable correlations arise: $e_{g,t}^{US}$ and $c_{g,t}^{US}$ are positively correlated (0.52), $p_{g,t}^{US}$ is negatively correlated to $c_{g,t}^{US}$ (–0.36) and $e_{g,t}^{US}$ and $h_{g,t}^{US}$ are positively correlated (0.30). These correlations are significant and reflect that excess credit tends to be negatively related to macro sentiment within the economy. Granger causality in Table 5.2 indicates two-way causality between $e_{g,t}^{US}$ and $c_{g,t}^{US}$, the significance from equity to sentiment

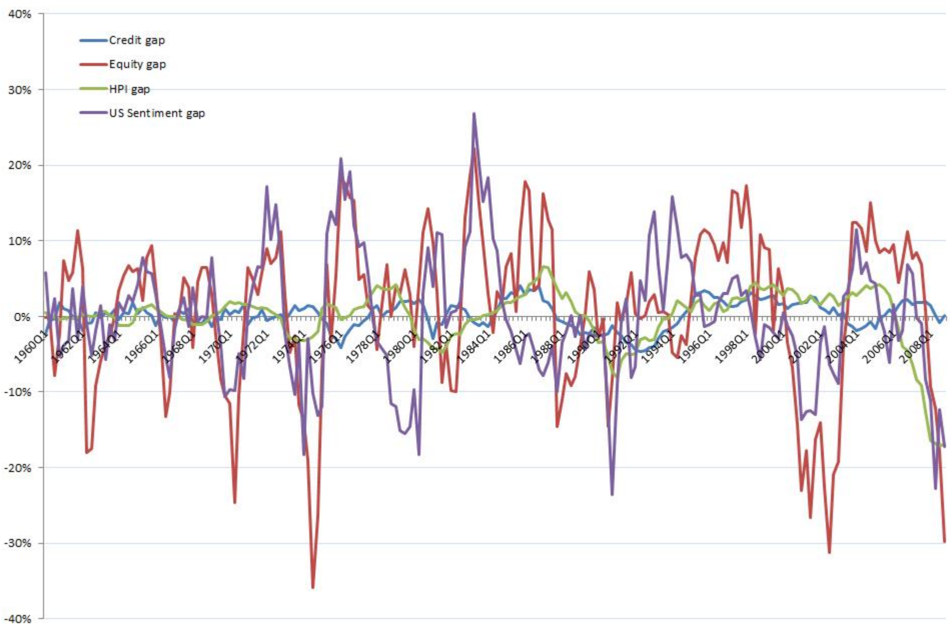

Figure 2.10: All time series data gaps for US quarterly data are displayed over the entire period.

is slightly greater. It is also the case that $c_{g,t}^{US}$ Granger-causes $p_{g,t}^{US}$ which implies that macro sentiment affects private credit. This is an additional affirmation of the impact of sentiment on consumption behaviour. Granger causality runs from $h_{g,t}^{US}$ to $c_{g,t}^{US}$ but not in the reverse direction. $e_{g,t}^{US}$ Granger-causes both $p_{g,t}^{US}$, and to a lesser extent $h_{g,t}^{US}$. Thus, sentiment appears to be a useful leading indicator in the EWS in this instance.

2.4.3 UK Crisis Prediction

According to Laeven & Valencia (2008), the UK suffered a systemic banking crisis in 2007. Northern Rock received a liquidity support facility on 14 September 2007 from the Bank of England due to difficulties associated with the subprime mortgage crisis. The bank experienced a run until a government bank guarantee was issued three days later. According to the updated version of Caprio & Klingebiel (1999), a secondary banking crisis occurred during 1974–1976, another in the 1980s and then in the 1990s. Notable bank failures included Johnson Matthey (1984), Bank of Credit and Commerce International (1991), and Barings (1995). Annual data can be seen in Figure 2.11: real credit growth reached a maximum of 83.9% in 1983. This was next followed by 18.3% in 1988. The p_t^{UK} and p_T^{UK} had been increasing steadily since the early 1990s. $p_{g,t}^{UK}$ peaked at 29% in 2008, followed by 28% in 1986 and 23% in 1989.

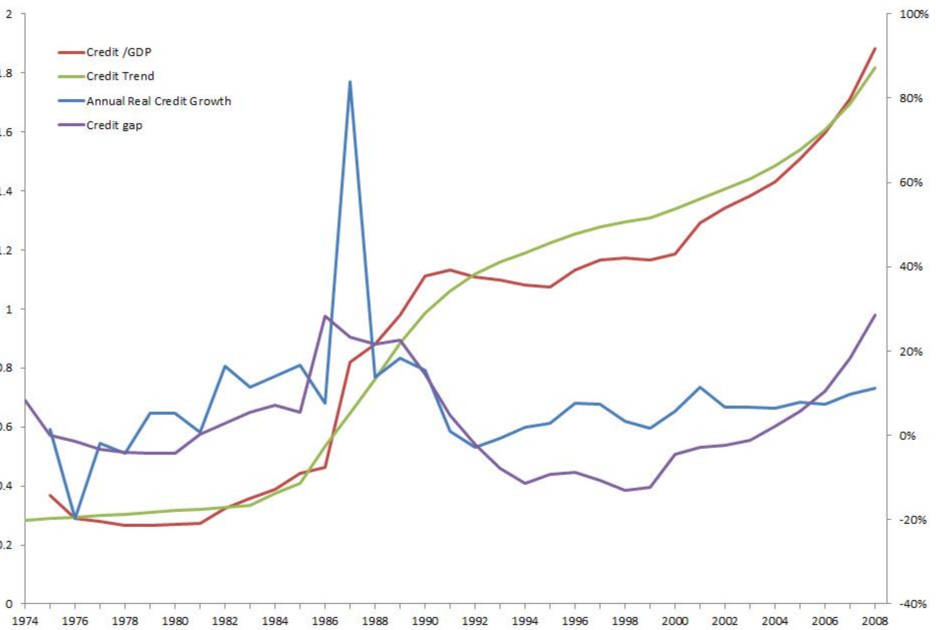

Figure 2.11: Annual ratio of private credit to GDP and trend (left axis), real credit growth and the credit gap (right axis) for the UK over the period.

Figure 2.12 shows the $p_{g,t}^{UK}$, $e_{g,t}^{UK}$ and $h_{g,t}^{UK}$ gaps. Prior to 2007, $p_{g,t}^{UK}$ and $h_{g,t}^{UK}$ were both elevated. The $e_{g,t}^{UK}$ was minimal and would not have been an indicator for this crisis. $e_{g,t}^{UK}$ tends to peak before $h_{g,t}^{UK}$. In 2004, the $h_{g,t}^{UK}$ measured 34% which subsequently dropped to 25% in 2005. $e_{g,t}^{UK}$ peaked at 24% in 1999. $p_{g,t}^{UK}$ reach a 15% in 2007 followed by 29% in 2008. The only other comparable year was 1986 when it reached 28%. From the gaps in Table 2.8, one can see that $p_{g,t}^{UK}$ was not as large as was for the case in the US. $h_{g,t}^{UK}$ and the $p_{g,t}^{UK}$ are both useful indicators in this instance. Once again, even though the annual returns are positive, the $e_{g,t}^{UK}$ is ineffective. Given the fact that the crisis was a result of asset price inflation which pertained to property, this is not unexpected. The results for quarterly data which include macro sentiment are in the Appendix in Table 5.2.

Table 2.8: Indicator gaps and nominal annual equity returns R_t five years prior to and during the year of the crisis within the UK.

Year	$p_{g,t}^{UK}$	$e_{g,t}^{UK}$	$h_{g,t}^{UK}$	R_t
2003	–1%	–34%	33%	–17%
2004	2%	–23%	34%	9%
2005	6%	–17%	25%	18%
2006	10%	–5%	19%	13%
2007	18%	2%	15%	2%

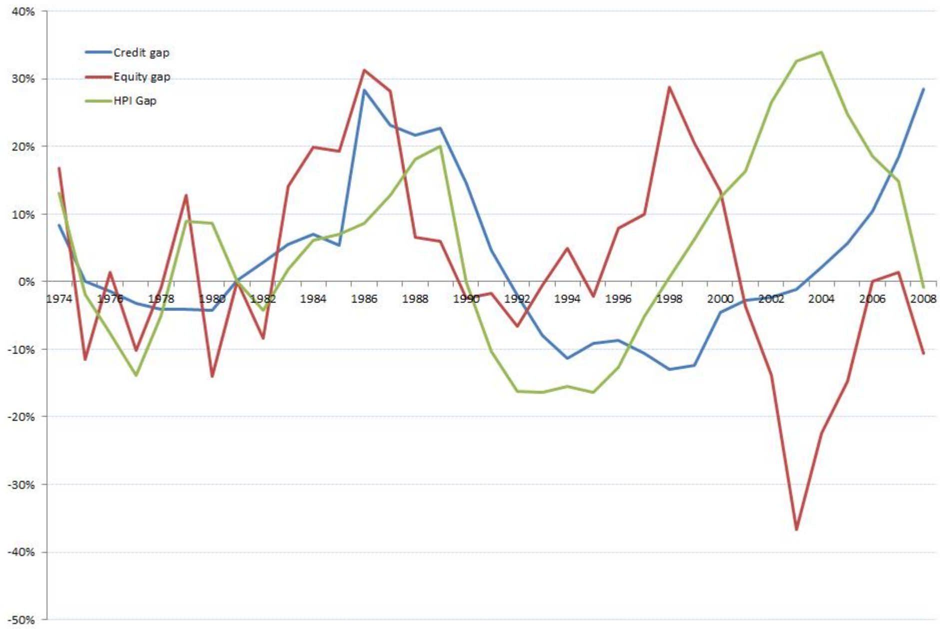

Figure 2.12: The UK annual credit, real equity and real HPI gap from 1974 to 2008.

Increasing the frequency to quarterly, the data yield a slightly different result to that seen in the case of the US. The difference in construction between the CS^{US} and CS^{UK} requires the latter to be adjusted by adding 100 to shift the series on the y-axis to ensure positivity for the application of the HP filter. $p_{g,t}^{UK}$ is far in excess of the 4% suggested in BL. $h_{g,t}^{UK}$ peaked at 18% in 2003, and declined thereafter. $e_{g,t}^{UK}$ was at a maximum of 19% in 2006, half of the suggested 40% for the asset gap. Figure 2.13 shows quarterly gaps for all series. One can see there are certain gaps that appear to move synchronously; taking this one step further, the positive correlation between $h_{g,t}^{UK}$ and $p_{g,t}^{UK}$ is 0.43 for this period, $e_{g,t}^{UK}$ and $c_{g,t}^{UK}$ are also positively correlated (0.41). $p_{g,t}^{UK}$ and $c_{g,t}^{UK}$ are negatively correlated (–0.26). Granger causality using two lags indicated that there is two-way causality between $h_{g,t}^{UK}$ and the adjusted $c_{g,t}^{UK}$ (both p-values were less than 1%). Thus, this is a simple illustration of the interaction between these gaps that may be instrumental for future developments within the macroeconomy and sentiment.

2.5 Conclusion and Practical Applications

The contribution of this chapter has been to merge macro sentiment, defined as consumer sentiment, with other significant macro data releases as a means to forecast financial instability.

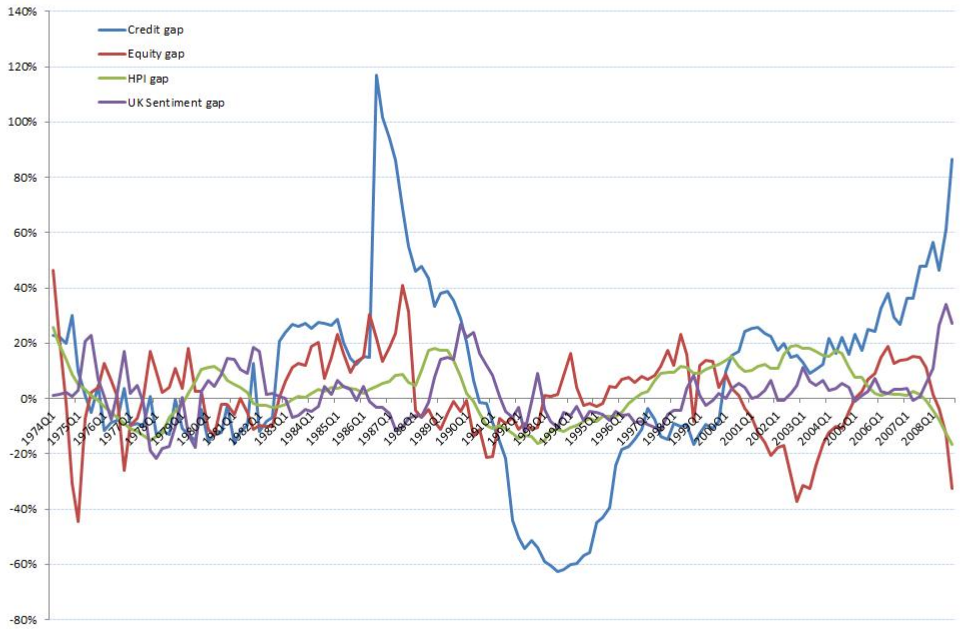

Figure 2.13: UK quarterly gaps for all series between January 1974 and December 2008.

An additional contribution is the use of the inflation-adjusted Case-Shiller HPI for the US, and Nationwide HPI for the UK, as a reflection of the residential property market for the respective countries. Previous research has focussed solely of data-driven time series. This chapter has extended an existing EWS by including an additional unexamined variable. Additionally, the contagion effects which have not been addressed within the framework, may be considered given the contribution based on sentiment contagion via bilateral trade relations, as discussed in §2.2.3.

Central to this research is the relevance of macro sentiment as a leading indicator pertaining to systemic crises. Quarterly data for the US and UK has been incorporated into the BL EWS to yield results to affirm the hypothesis. In addition to this, the research has shown bilateral relationships between macro sentiment and trade. In section 2.2.3, it has been established that US sentiment Granger-causes UK sentiment. This is extended by considering strength of trade – both total and bilateral. Results confirm that trade-related variables Granger-cause macro sentiment. The strength of the bilateral trade relationship appears to increase over time from the US to the UK. That is, the US is a dominant factor and has influence on the UK beyond that of a financial nature. Two-way Granger causality was shown to exist in the UK between macro sentiment and total trade strength. This was not the case for the US.

The BL framework is a non-parametric signal extraction method which monitors the buildup of imbalances within an economy. It is an intuitive approach which establishes the relative stability of a given economy to predetermined threshold values. The quarterly data frequency limits the suitability to systemic crises, and hence it will likely not be able to forecast contagion which may arise from bank runs. The framework also fails to account for linkages between countries which are of consequence. Empirically, the application of the HP filter is slightly controversial as the annual and quarterly results tend to differ substantially when examining credit, equity and property variables.

Considering sentiment data, the HP filter accounts for the buildup of an imbalance in sentiment; although it has been shown that sentiment in both the US and the UK represents information contained in other economic variables, there is an unexplained component which may be attributed to emotions based on other factors. Quarterly results confirm that the macro sentiment gaps, which are deviations from what may be perceived as 'rational' sentiment, may assist in the early detection of financial instability. Excess pessimism in the quarters (between one and three years) leading up to identified banking crises indicate that instability can be more thoroughly gauged by examining deviations of sentiment from trend.

Extending these findings, the time series of quarterly indicator gaps for the US and UK are examined. The real equity and macro sentiment gaps are positively correlated thereby validating the results considering the positive contemporaneous relationship between aggregate market returns and sentiment. The credit gap and sentiment gaps are negatively correlated; in the case of the US, sentiment Granger-causes the credit and equity indicator gaps. In the UK, sentiment significance is limited to two-way causality with reference to the house price gap.

There are limitations to results pertaining to the EWS. The sample size of both countries and crises identified imply one cannot assert that these results will hold out of sample. In addition to this, limited macro sentiment data are available to allow for this extension to other developed countries or emerging markets. In the latter instance, the relevance of macro sentiment may be less plausible as crises may be a result of spillover effects from other countries within the region or possibly from currency markets due to shifts in risk appetite. This will be explored in Chapter 4 as a *Theory of Sentiment Propagation* is proposed. Given the sentiment–trade relationships in section 2.2.3, one possible channel through which macro sentiment may diffuse between countries is trade links. Financial markets are a more immediate manifestation of sentiment as capital flows are the means by which asset allocation is achieved to adjust for shifts in risk appetite.

Laeven & Valencia (2008) cite international capital mobility as a cause of international banking crises. Financial liberalisation also tends to increase the conditional probability of banking crises; this tends to be followed by increased capital flows.

This chapter has depicted the contribution of consumer sentiment to the determination of financial instability. Thus in practice, the general signalling approach may be extended to incorporate macro sentiment. Survey-based sentiment has been shown to forecast consumers' perceptions of future economic activity. The use thereof within the EWS has consistently shown to exhibit pessimism prior to the identified periods of financial instability. In practice, this information should be incorporated to more accurately identify future episodes of financial instability. Additionally, the contagion effects that arise between countries may be captured by the causality of sentiment, as observed in §2.2.3. Given that financial market integration has often been associated with spillover effects, those bilateral trade relations which form a significant part of a country's GDP have been shown to affect sentiment of the countries involved. Therefore, examining financial instability of a country in isolation may be flawed. Macro sentiment appears to reflect contagion effects between countries, based on trade. The effect of high-frequency fund flows to such instability shall be discussed in chapter 4. The information content therein, is too highly relevant to contagion.

Chapter 3

Institutional Investor Sentiment: The Options

3.1 Introduction

Investor sentiment should necessarily refer to the active participants within financial markets. The title 'consumer sentiment' renders macro sentiment ill-suited to capture investors' perceptions of current and expected aggregate market movements. However, congruous opinions are expected when examined at the same granularity given the relationship between the aggregate equity market, the macroeconomy and macro sentiment. The exact definition of sentiment is contextual as the notion on its own is vague. The applicability in all instances is subject to the select group of investors. Extensive ongoing analysis with respect to the aggregate market and popular culture have both contributed to the endurance of a select few measures. This will be addressed in section 3.2. Behavioural models hypothesise that sentiment can be gauged as a correction to under- or over-reaction of noise traders' aggregate errors in beliefs, and therefore empiricists seek out a contrarian relationship between returns and the identified sentiment measure over varying time horizons **?**. Controversy often arises in the instance of returns predictability. Short-run predictability would lead to trading strategies that may generate abnormal returns, and is therefore an unlikely scenario assuming there are limits to arbitrage. The lack of predictability in the near-term, however, does not imply that sentiment is ineffectual. Sentiment may drive asset prices away from intrinsic value for extended periods of time, which is likely to be evident in the correction. Additionally, but not to be discussed here, sentiment effects are predicted in the cross-section of stocks. This research is primarily concerned with the measurement of sentiment, both direct and indirect, which pertains to institutional investors within the US equity markets.

Derivative securities provide a rich source of information to gauge market sentiment (Bahra 1997). Academic researchers and central banks have used implied risk-neutral distributions to discern market expectations pertaining to the distribution of the underlying at the relevant maturity. Option prices capture forward-looking risk-neutral probabilities of the underlying and thereby provide an ex ante measure of investors' beliefs (Alonso, Blanco & Rubio 2006). Shefrin (1999) argues that options markets are particularly vulnerable to investor sentiment which leads to inefficiencies. As the strength of bullish sentiment is equivalent to that of the bearish sentiment, bulls overbid prices of index call options whilst the bears overbid the prices of index put options. [1] This then leads to the observed implied volatility smile. Derivatives are used for both risk management as well as speculation due to the advantage of leverage. The high potential returns and limited liability, as well as the frictions associated with hedging by liquidity suppliers, suggest that investor sentiment influences trading and, consequently, prices of options on both large and small stocks. Index options are deemed particularly susceptible to the sentiment of institutional investor whereas retail investor sentiment is manifest in single stock options.

Since there is a rich cross-section of options traded on the same underlying index for numerous maturities, sentiment-driven mispricing in option prices may be identified. Bullish investors tend to take long positions in index calls, while bearish investors take long positions in index puts (in general stock options). In contrast, they may partially cancel each other in the stock market. It is easy to create and destroy contracts in the option market while the supply of stock is fixed (at least in the short run). Thus, option markets can provide a clearer picture of different groups of investors' absolute sentiment while the stock market reflects investors' relative demand. The no-arbitrage relation between stock and options, and the extensive literature on rational option pricing models provide a benchmark for the fair value of options. In the stock market, the fair value is more subjective and harder to accurately determine (Han 2007).

European options of a particular maturity and range of strikes can be used to calculate the implied risk-neutral probability distribution. The difference in price between two call options

[1] Shefrin mentions the argument proposed by Fama (1997) stating that investors' under-reaction and over-reaction is cancelled out, resulting in efficient markets.

of the same maturity written on the same underlying, which have adjacent strikes, reflects the value attached to the ability to exercise the options when the underlying asset lies between their strikes. This depends on the probability of the asset ending up in this interval at maturity. Thus prices of these options are related to weights attached by the representative risk-neutral investor to the possible outcome for the terminal value of the asset. A suitable combination of European call options can then be used to infer Arrow–Debreu (state-contingent) prices.

The idea of risk-neutrality is pervasive in finance literature. It forms the basis of the pricing argument behind the indifference between an option and the hedge portfolio (delta units of the underlying and the risk-free asset). Investors are risk-neutral if they are indifferent to risk. Risk-neutrality is tantamount to an expected return on all assets of the risk-free rate of interest. Thus, investors require no risk premium for their investments. An investor is risk-neutral if he/she has a linear utility function. The risk-neutral distribution of an underlying asset is equal to the market's beliefs regarding the distribution of the asset's return, adjusted for risk aversion. It is determined by the investor's subjective probability density of the underlying asset's future returns and the investor's risk preferences.

The slope of the implied volatility function for index options has been related to the survey-based measure of institutional investor sentiment (Han 2007, Lemmon & Ni 2008). If sentiment about the stock market shifts to bearish or less optimistic regarding future equity performance, a greater demand for portfolio insurance and equivalently, out-the-money index put options, should follow. Bollen & Whaley (2004) show that demand pressure in option markets affects prices, thus a more bearish sentiment may lead to more expensive out-the-money index puts, evidenced in the steeper implied volatility smile. This also implies that the index risk-neutral skewness decreases which is tantamount to a decrease in the slope of the pricing kernel. This is further explained in section 3.2.2.

Gemmill & Saflekos (2000) investigate the usefulness of the risk-neutral distribution of FTSE-100 index options over the period 1987–1997 for forecasting, hedging purposes or to determine the current sentiment of investors. They find that it may reveal market sentiment which could be useful for the policy stance of monetary authorities or contrarian investors. Their analysis indicated that the distribution reflected market sentiment during elections. Generally, the implied distribution is left-skewed and its shape changes frequently. The authors conclude that a plausible explanation is portfolio-insuring behaviour which reflects both recent moves in the stock market, and investor preferences.

This research seeks to affirm the use of sentiment-related measures derived from the aggregate equity market index option-implied returns distribution. The assumption is that the beliefs of institutional investors can be gauged by both the risk-neutral probabilities, and third moment (skew) associated with the index returns distribution at the relevant maturity. The cumulative probability measure at time t, associated with the index ending at or below the at-the-money futures level for some maturity T, denoted $p_{t,T}^{RND}$ is to be examined. That is, $p_{t,T}^{RND} = \mathbb{P}[S_T \leq F_{t,T}]$ is constructed, where S_T refers to the index at maturity date T and $F_{t,T}$ is the current time t futures level for maturity date T. Additionally, the implied skew denoted $\eta_{t,T}^3$, based on the fully non-parametric method applied to extract the RND, will be examined. Here, T refers to a 30-day period and therefore necessitates interpolation using appropriate maturity options; the S&P 500 index reflects the aggregate equity market. The implied risk-neutral distribution is inferred from the associated European index options (SPX) using a fully non-parametric method (Bondarenko 2003). This is briefly discussed in section 3.3.3. This method gives rise to a probability distribution of the underlying index for a given maturity; once converted to a returns distribution, the skew which is termed the 'third robust moment', can be calculated. Further details are in section 3.4.

In order to assess performance, weekly regressions are performed using these measures as well as that of institutional investor sentiment (bull–bear spread); daily data using other related measures are also examined: The CBOE Volatility Index, a modified version of the CBOE put–call option volume ratio, the model-free option-implied skew of Bakshi et al. (2003) (BKM) and the smirk of Xing, Zhang & Zhao (2008). These are introduced in section 3.2.2. The relationship to the underling index is also discussed when appropriate. The proposition is such that the daily probability measure $p_{t,T}^{RND}$ is the true reflection of institutional investors sentiment. The frequency deems the use thereof more current than the analogous survey measure. It is necessarily dependent on the numerical method applied to index option prices; however, the method applied here is superior to other methods, as discussed by Bondarenko (2003).

This chapter is organised as follows. Section 3.2 discusses investor sentiment measures with an emphasis on those which are of relevance here; section 3.3 is a concise yet pertinent exploration of risk-neutral option pricing. The means to extract the distribution is introduced followed by an explanation of those methods employed to calculate $\eta_{t,T}^3$, the BKM skew, and the smirk.

The empirical analysis follows in section 3.5: data used are detailed in section 3.5.1, the process applied to 'clean' the index options follows in section 3.5.2. This is then followed by daily and weekly results. For each variable included in the analysis, section 3.6 provides an interpretation of the relationships that are shown to exist. Section 3.7 concludes.

3.2 Investor Sentiment

Financial market (investor) sentiment is either a direct survey-based measure, or an indirect quantification of trade-related data which aggregates the collective behaviour of those participants. These measures often pertain to either retail or institutional investors and are available at varying frequencies. Indices derived from surveys of both investor groups are usually available weekly; financial market data are available at much higher frequencies and therefore, likely more relevant. The monthly macro sentiment index is lagged with respect to financial markets and is therefore inappropriate to gauge current investor sentiment. Having explored the link between aggregate equity markets and macro sentiment, it appears that the sentiment index is a momentum variable and the stock market is a leading indicator. However, further investigation in Schmeling (2009) finds that macro sentiment does in fact forecast aggregate market returns in the long run: consumer sentiment is a contrarian indicator. Results in general are subject to the empirical method employed and the samples used. Given that the mispricings which arise due to sentiment are persistent in the instance that limits to arbitrage do exist, a longer unknown horizon may be required to observe the corrections. The indirect measures can be further separated into stock- and option-derived measures.

Sentiment-related research can be classified as one of four strands: the first examines a contender variable (or a composite index) with justification, and makes a comparison to other widely accepted measures, thereby seeking affirmation of its validity and possible superiority. The second strand of the literature examines the time series relationship of the selected indicator variable to the aggregate market. The third strand combines the first two. The final strand examines sentiment effects in the cross-section and attempts to find a stock's sensitivity to sentiment, according to the measure employed. This research is primarily concerned with the first strand, and therefore reference to the effect of sentiment as a means to forecast returns in the aggregate or cross-section will not be discussed in detail.

Consumer sentiment is often the reference sentiment measure with which to determine the relative performance of an identified sentiment variable, insofar as the latter can be sensibly interpreted with respect to the sentiment of the investor group. The following section reviews a few notable direct investor sentiment measures. This research is primarily concerned with institutional investor sentiment, and therefore the emphasis will be placed on related measures. Institutional investor sentiment is tantamount to portfolio insurance. The direct survey-based measure to be used in the empirical section will be the Investors Intelligence weekly measure. In the instance of the indirect measures, option-related measures will be reviewed; other measures are listed briefly.

3.2.1 Surveys Index Measures

Survey-based sentiment indicators include, but are not limited to, the Gallup Index of Investor Optimism, the American Association of Individual Investors (AAII) Sentiment Survey and the Investors Intelligence (II) Survey published by Chartcraft. The AAII survey is a direct measure of retail investor sentiment and the II is corresponding measure for institutional investors. The latter is of particular relevance to the research given the reference investor group.

American Association of Individual Investors Survey

The AAII polls a random sample of its members each week. [2] The association asks each participant where they think the stock market will be in six months: up, down or the same. AAII then labels these responses as bullish, bearish or neutral, respectively. The weekly survey started in 1987 conducted by postal service; it has been replaced with an online version since 2000. Results are available on the AAII website and are also published in Barron's. Thorp (2004) shows that the survey is best used as a contrarian measure as peaks often precede market declines (S&P 500 index). Providing event-specific instances, AAII conclude that 'Indicators such as this are best used in tandem with others so that you receive confirming signals of potential market movements.'

In support of this, Fisher & Statman (2000) examine sentiment pertaining to large (Wall Street strategists), medium (II survey) and small (AAII survey) groups of investors. They find that individual investors become bullish following the increased bullishness of newsletter writers; this is not completely synchronous. Monthly data suggests the level of sentiment of individual investors

[2] `http://www.aaii.com/`

is a reliable contrarian indicator of future S&P 500 returns; there is a negative and statistically significant relationship between the sentiment level of individual investors and S&P 500 returns in the following month.

Investors Intelligence Survey

The II is a survey based on 150 newsletters (those not affiliated with brokerage houses or mutual funds) which are classified as bullish, bearish or waiting for correction. The survey was published monthly from 1963, and then bi-weekly through to June 1969. Thereafter, it shifted to a weekly schedule.[3]

Literature which seeks to use the II survey measure is mixed. Earlier research includes that of Solt & Statman (1988) and Clarke & Statman (1998). Their results suggest that the II survey, although considered a contrarian indicator, cannot be used to forecast aggregate market returns. They find no statistically significant relationship between sentiment and subsequent returns of the S&P 500. Further, they examined the effect of increased volatility on the index, examining whether heightened uncertainty result in increased bearishness. Over a four-week period, they find a positive statistically insignificant relationship between volatility and bullishness: positive total returns over a period along with high daily volatility of returns within that rendered subjects slightly less bullish than the same positive total returns with low volatility. Hence, volatility did not lead newsletter writers into bearishness. Instead, it obscures both positive and negative returns. Newsletter writers did not alter their ways of forecasting post the 1987 crash; they did not see declines in stock prices as buying opportunities either before or after the market crash. Fisher & Statman (2000) find no clear relationship between large-cap stock returns and the level of sentiment of newsletter writers.

Lee, Jiang & Indro (2002) examine the relationship between market volatility, excess returns, and investor sentiment for three different market indices, the (DJIA) (Dow Jones Industrial Average),[4] the S&P 500 Index and the NASDAQ (National Association of Securities Dealers Automated Quotation), from the beginning of 1973 through 6 October 1995. They use the II sentiment index as a direct measure of investor sentiment. Their main findings suggest that sentiment is a significant factor in explaining equity excess returns and conditional volatility.

[3] `http://www.investorsintelligence.com/x/advisors_sentiment.html`

[4] The DJIA is a price-weighted average of 30 large blue-chip stocks.

Their results consistently show that sentiment is a risk factor that is priced in. Excess returns are contemporaneously positively correlated with shifts in sentiment. Furthermore, the magnitude of the shift in sentiment has a significant impact on the formation of conditional volatility of returns and expected returns. Bullish (bearish) shifts in sentiment lead to downward (upward) revisions in the volatility of returns and are associated with higher (lower) future excess returns. The significance of investor sentiment in explaining the formation of conditional volatility and expected return is robust across different indices and subperiods.

Brown & Cliff (2005) relate sentiment levels to stock price deviations from fundamental value and examine the long-run effects of sentiment on stock returns. [5] Brown and Cliff use monthly II survey data from January 1963 to December 2000 and the returns pertain to the Fama–French portfolios based on common factors, defining the bull–bear spread as the percentage of bullish minus bearish newsletter writers. They relate the level of sentiment to market mispricing as estimated by the Dow Jones Industrial Average pricing errors (Bakshi & Chen 2005).

Brown and Cliff assume that a subset of investors, speculators, are subject to extreme optimism (or pessimism) and adjust their asset valuations accordingly. The alternative group, the fundamentalists, are unbiased in their assessment. Market prices are therefore a weighted average of these groups with weights reflecting the share of ownership of the respective groups. Limits to arbitrage hinder the exploitation of perceived asset mispricing. Thus market prices may differ from intrinsic value for protracted periods of time. Excessive optimism leads to the overvaluation of assets. Therefore, the reversion to intrinsic values over the long run implies low or negative returns.

Sentiment is persistent, suggesting that bouts of optimism or pessimism reinforce themselves. It is also strongly correlated with contemporaneous market returns and not useful in predicting subsequent near-term returns. [6]

Brown and Cliff's results indicate that for larger firms or low book/market firms, sentiment is a significant predictor of future returns at the one-, two-, and three-year horizon. Since these

[5] Solt & Statman (1988),Clarke & Statman (1998),Fisher & Statman (2000),Brown & Cliff (2004) use survey data but focus on the short-run implications.

[6] To control for rational expectations, Brown and Cliff use the following variables: the stochastically detrended one-month US Treasury bill return, the difference in monthly returns on three-month and one-month T-bills, the term spread as measured by the spread in yields on the 10-year US Treasury bond and the three-month T-bill, the default spread measured as the difference in yields on Baa and Aaa corporate bonds, the dividend yield for the value-weighted CRSP index over the past 12 months and the rate of inflation.

portfolios represent most of the market capitalisation, the market portfolio is also significantly affected by sentiment (significant at the 5% level for one and two years and at the 1% level for three years). Their results are consistent with behavioural models that suggest prices under-react in the short run and over-react in the long run.

Wang, Keswani & Taylor (2006) examine the relationship between returns, volatility and sentiment. The noise trader approach to finance implies that sentiment affects returns. Evidence suggests that returns in fact affect sentiment. Therefore, they propose that volatility possibly affects sentiment too. Their weekly analysis includes the survey measures of AAII and II, as well as other option-related sentiment variables. Analysing both levels and first differences, results indicate that sentiment is caused by returns and also by realised volatility.

The II survey measure is often a reference measure for the performance of other indirect market sentiment measures. It appears that the individual survey results of AAII tend to lag those of the II, and therefore the survey respondents of II may either be more informed at a given time or have the ability to influence the opinions of retail investors. The surveys appear to be lagged momentum variables and are both considered contrarian. The II bull–bear spread is the survey-based measure used to represent institutional investor sentiment in section 3.5.4.

3.2.2 Market Measures of Investor Sentiment

These measures for both investor groups are derived from either market performance data, which are in fact technical indicators, or derivative market data. Market performance indicators include the ARMS index,[7] the number of new highs to new lows, the ratio of odd-lot sales to purchases, the percentage change in margin borrowing and the percentage change in short interest (Brown & Cliff 2004). Mutual fund flows are also an oft-cited measure that will be discussed extensively in the following chapter. Derivative market indicators include, but are not limited to, the CBOE put–call trading volume ratio, the CBOE Volatility Index, and the risk-neutral option-implied skew.

Some research aggregates a selection of such variables to form an index based on the first principal component. Composite measures include the sentiment index constructed by Baker & Wurgler (2006): the index is based on sentiment proxies that have been orthogonalised to several

[7] This measure is the ratio of the number of advances to declines standardised by their respective volumes.

macroeconomic variables which are visibly aligned to historical accounts of bubbles and crashes. Included are: the closed-end fund discount (Lee, Shleifer & Thaler 1990), the NYSE turnover, equity share in new issues, and number and average first-day returns of IPOs and the dividend premium.

Sentiment literature that examines one or more of the above measures is voluminous. However, few examine the merits of information to be gleaned from the associated risk-neutral distribution. This research is primarily concerned with institutional investor sentiment, and therefore the review is limited accordingly. Given that index options are a manifestation of the associated sentiment group, it follows that these instruments are non-redundant with respect to replication, and consequently sentiment. This research seeks to substantiate the use of option-implied measures, and therefore those identified sentiment measures will be reviewed below.

Put–Call Ratio

The daily ratio of the CBOE trading of equity puts to calls (PCR) is considered as a bearish indicator (Brown & Cliff 2004). The CBOE divides the sum of all call options, and the sum of all put options, that are traded each day on all individual equities as well as on various indices. A high ratio implies that the market has reached an oversold extreme and a turn might be at hand. To the contrary, a low ratio indicates that the market has reached an overbought condition and a price correction is expected. Market participants view the PCR as a fear indicator, with higher levels reflecting bearish sentiment. According to Bandopadhyaya & Jones (2006), a level of 0.8 is considered normal as calls are traded more frequently than puts. Accordingly, a relatively low level of the PCR is associated with a lower demand for puts or a greater demand for calls, which would reflect bullish sentiment (Simon & Wiggins III 2001).

In section 3.5, the PCR is derived using daily data exclusively from S&P 500 index options and therefore, the above analysis is an illustration of the validity of this measure.

CBOE Volatility Index

The Market Volatility Index (VIX) is a forward measure of expected volatility of the S&P 500 index and is often referenced as the 'investor fear gauge' (Chicago Board Options Exchange

2009).[8] The VIX is implied by the current prices of S&P 500 index options and represents expected future market volatility over the next 30 calendar days and is available on a real-time basis. The VIX was intended to provide an index upon which futures and options contracts on volatility could be written. The CBOE launched trading of VIX futures contracts in May 2004 and VIX option contracts in February 2006. The SPX option market became the most active index option market in the US, with the index option market being dominated by portfolio insurers who routinely buy OTM (out-the-money) and ATM (at-the-money) index puts for insurance purposes, and therefore the VIX is referenced as the price of portfolio insurance.

Simon & Wiggins III (2001) investigate the predictive power of the VIX, the PCR and ARMS index (TRIN)[9] for subsequent returns on the S&P 500 futures contract over 10-day, 20-day, and 30-day horizons from January 1989 through June 1999. Their empirical results indicate that these contrarian indicators have statistically and economically significant forecasting power. Periods of extreme fear in the stock market have proven to be favourable buying opportunities. In particular, they find that the VIX has a significant negative correlation with lagged S&P 500 returns, and when S&P 500 returns over the previous 10 days are in their lowest rather than highest deciles. This finding is consistent with the leverage effect, in which large negative stock market returns lead to higher subsequent volatility than equal magnitude positive stock market returns. In contrast to this, the PCR does not have a significantly negative correlation with lagged S&P returns or with the VIX and varies little across extremely strong and weak market environments and extremely high and low levels of the VIX. Weakness in S&P 500 futures leads to subsequent higher implied volatilities, more so than a greater trading volume in puts relative to calls.

Simon and Wiggins find that the VIX rises after the market has sold off sharply, which induces fear of further weakness. The greater level of fear causes market participants to bid up implied

[8] The generalised formula is given as

$$\sigma^2_{VIX} = \frac{2}{T}\sum_i \frac{\Delta K_i}{K_i^2} e^{rT} Q(K_i) - \frac{1}{T}\left[\frac{F}{K_0} - 1\right]^2,$$

where $VIX = 100 \times \sigma_{VIX}$, T is time to expiry, F is the forward index level derived from index option prices, K_0 is the first strike below F, K_i is the strike price of ith out-of-the-money option. For a call, this implies $K_i > K_0$, and for a put, $K_i < K_0$. ΔK_i refers to the average interval between strikes, r is the risk-free interest rate and $Q(K_i)$ is the midpoint of the bid–ask spread for each option with strike K_i.

[9] The TRIN index is calculated as

$$\text{TRIN} = \frac{\text{advancing issues/declining issues}}{\text{advancing volume/declining volume}}.$$

volatilities. In this environment, investors raise cash, which creates the fuel for a subsequent rally. A 1% point increase in the VIX is associated with a 0.2% increase in returns over the next 30 days. As the trading volume of puts rises relative to that of calls, subsequent returns of the S&P 500 futures tend to be higher.

Giot (2005) assesses the relationship between implied volatility and future stock returns. Specifically, the author focuses on the contemporaneous relationship between relative changes in implied volatility and stock market returns, as well as between implied volatility and future returns. In agreement with Whaley (2008), there is a negative and statistically significant relationship between the returns of the stock and the VIX. The relationship is asymmetric for the S&P 100 index:[10] negative stock index returns are associated with greater proportional changes in implied volatility measures than positive returns, the former being much stronger in a low-volatility environment. Giot also finds weak evidence that positive (negative) forward-looking returns are expected for long positions in the S&P 100 index, triggered by extremely high (low) levels of the implied volatility index.

Whaley (2008) notes that the VIX spikes during periods of market turmoil: if expected market volatility increases (decreases), investors demand higher (lower) rates of return on stocks, so stock prices fall (rise). Thus the relation between rate of change in the VIX should be proportional to the rate of return on the S&P 500 index. However, increased demand to buy index put options affects the level of VIX. Hence, the change in the VIX rises at a higher absolute rate when the stock market falls than when it rises.

The VIX is unequivocally an essential gauge of fear within financial markets. The fact that it is derived from the deep and active index options written on a large market capitalisation-weighted index renders it a prudent indication of institutional investor sentiment.

Risk-Neutral Skew

Han (2007) investigates whether investor sentiment (defined as the aggregate error in beliefs) affects S&P 500 index option prices by examining risk-neutral skewness. Using sentiment measures derived from survey data, market activity and valuation errors, the author relates the variation in the slope of the index volatility smile to changes in market sentiment. Institutional sentiment

[10]The VIX was constructed using the S&P 100 index until 2003 after which the methodology was revised.

measures include the II bull–bear spread, the net position of large speculators in S&P 500 futures and valuation errors of the S&P 500 index. The paper focuses on the effect of investor sentiment on the options market. The empirical analysis examines the time series relation between sentiment and the risk-neutral skewness of the implied distribution of the monthly index returns from January 1988 to June 1997. Applying the method of Bakshi et al. (2003), a model-free estimate of risk-neutral skewness is extracted on a given date from the cross-section of index option prices. The risk-neutral skewness is determined by the slope of the pricing kernel. The ratio of the risk-neutral probability density and the empirical probability density, discounted at the risk-free rate, is referred to as the pricing kernel or stochastic discount factor. Equivalently, the value of the pricing kernel at a given state is the corresponding Arrow–Debreu state price per unit probability. The pricing kernel provides a unifying framework for all asset pricing theories. Thus the study determines whether sentiment affects the slope of the pricing kernel.

Since bearish investors will pay more for state-contingent claims which provide a payoff when the index level is low, the increased demand leads to a more negatively sloped pricing kernel. A necessary condition for non-fundamental variables such as investor sentiment to affect the pricing kernel is that there are limits to arbitrage in the financial markets: these limits exist due to noise trader risk, trading frictions, a short investment horizon and limited capital on the part of arbitrageurs. Han finds that the implied risk-neutral distribution for the index return is more negatively skewed when market sentiment reverts to being more bearish; this can be seen in a steepening of the option volatility smile of a particular maturity. The results hold after controlling for a set of rational factors which may affect sentiment.

Bollen & Whaley (2004) have examined the effect of net buying pressure [11] on the shape of the implied volatility function (IVF) for both index and stock options. Seeing that the volatility parameter in the Black–Scholes option pricing equation is a function of strike and time to maturity, there have been various attempts to modify the underlying stochastic process to account for the non-lognormal return distribution. However, Bollen and Whaley note that the IVF derived from such procedures cannot account for the time series variation in option prices or equivalently, the IVF. Therefore, they investigate investors' supply and demand for different option series. [12] Due to an upward sloping supply curve and limits to arbitrage, market makers charge higher prices

[11] The net buying pressure is defined as the difference between the number of buyer-motivated contracts traded each day and the number of seller-motivated contracts. Trades executed above (below) the bid/ask midpoint are considered buyer-motivated (seller-motivated).

[12] An option series is defined by the following three characteristics: call or put, strike and expiry.

as hedging costs and/or volatility-risk exposure increases. Implied volatility varies according to public demand for a particular option series. With reference to S&P 500 index (SPX) options, institutional investors buy index puts as portfolio insurance. Since there are no natural counterparties, market makers absorb the imbalance. With an upward sloping supply curve, implied volatility will exceed actual return volatility – the difference will be due to costs associated with the hedging portfolio or risk exposure. Their overall results suggest that net buying pressure is an important determinant of the shape of the IVF, particularly for SPX options where public order imbalances are greatest. Therefore, prices of SPX options will fluctuate as demand and supply varies.

Xing et al. (2008) (XZZ) examine the shape of the volatility smirk defined as the difference between OTM put and the ATM call option-implied volatilities. In the cross-section, they find that stocks which exhibit the steepest smirks underperform those stocks with the least pronounced smirks, on a risk-adjusted basis using the Fama–French three-factor model (Fama & French 1996). The predictability persists for up to six months hence. This is consistent with informed investors that trade OTM puts as a means to incorporate bad news into prices. Due to the different characteristics of the stock and options markets, information may be incorporated in one market more promptly than the other. Hence, a lead–lag relationship may exist between asset markets. Since options provide leverage, it may be the leading market.

Given that institutional investors trade index options as a means to insure against aggregate market declines, the use of index option-implied skew as a measure of sentiment follows from the supply–demand implied volatility curve relation as well as the effect of sentiment on option prices. Therefore, the research examines the skew and the probability measure p_t^{RND}, which will be described in section 3.4, in relation to the bull–bear spread of the II survey, the VIX, the PCR pertaining exclusively to the S&P 500 index options, and the smirk of XZZ. To proceed, risk-neutrality is briefly discussed in section 3.3.1.

3.3 Index Option Theory

3.3.1 Risk-Neutrality

In the absence of arbitrage, the expected payoff of a contingent claim under the risk-neutral measure is the risk-free rate of return. All physical probabilities are adjusted which translates into pricing all derivatives under the risk-neutral or equivalent martingale measure. A market is said to be complete if every claim in the market is attainable (can be replicated). Given complete markets, in the absence of arbitrage, this measure is unique (Bingham & Kiesel 2004). [13]

There are a number of practical issues when one considers risk-neutral valuation in continuous time. Continuous rebalancing of the hedge is assumed: delta is constantly changing so one is required to buy or sell the underlying to maintain a risk-free position. The underlying has to be consistent with certain assumptions, such as being in Brownian motion without any jumps, and with known volatility. Attempting to specify a stochastic process for the underlying which is more a reflection of actuality than a requirement for mathematical elegance, often results in an implied returns distribution which is non-lognormal.

The model assumptions are somewhat unrealistic and therefore the option pricing formula of Black & Scholes (1973) is viewed more appropriately as a mapping from observed price to the volatility parameter, or implied volatility. However, to price options which are path dependent, a model for the underlying process is often necessary. Analogously, the theory also permits the reverse process of observing the distribution for the underlying – that is, it allows for the extraction of the implied returns distribution at some terminal date from observed European option prices. Thus, for some maturity, all available implied volatilities of European options can be used to infer the underlying distribution process.

Risk-neutral valuation exploits the perfect correlation between the changes in the value of an option and its underlying asset. As long as the underlying is the only random factor, then this

[13] A contingent claim X is attainable if there exists a replicating strategy $\psi \in \Psi$ such that $V_\psi(T) = X$. In an arbitrage free market, the price of a contingent claim is given by the value process of the replicating strategy. The arbitrage price process of any attainable contingent claim X is given by the risk-neutral valuation formula

$$\pi_X(t) = \beta(t)^{-1}\mathbb{E}^Q\left[X\beta(T)|\mathcal{F}_t\right] \qquad \forall t = 0,\ 1, \ldots, T,$$

where $\mathbb{E}^Q$ is the expectation operator with respect to the equivalent martingale measure $\mathbb{Q}$. Here, $\beta(\cdot)$ refers to the risk-free asset.

correlation should be perfect. Thus if an option goes up in value with a rise in the stock, then a long option and sufficiently short stock position (delta) should not have any random fluctuations as the stock hedges the option. The resulting portfolio is said to be risk-free. If one hedges correctly in a Black–Scholes world, all risk is eliminated, and therefore no compensation for risk is required. Thus under the martingale measure, assets appreciate at the risk-free rate.

3.3.2 The Risk-Neutral Distribution

Prices of traded options provide an ex ante source of information about the underlying price process. There are usually quite an extensive number of option contracts for any underlying on a given day available. The prices of those options encapsulate market sentiment regarding the distribution of the underlying at the terminal date as well as investors' risk preferences. Let S_t denote the price of the underlying at time t (a trading date), and let $Z(S_T)$ be a European-style option payoff with maturity date T. In the absence of dividends, the European call $C_{t,T}(K)$ and put $P_{t,T}(K)$ Black–Scholes option price Z_t at time t, written on the underlying with asset price S_t, are given as

$$\begin{aligned} C_{t,T}(K) &= S_t\Phi(d_1) - e^{-r_\tau \tau} K\Phi(d_2), \\ P_{t,T}(K) &= e^{-r_\tau \tau} K\Phi(-d_2) - S_t\Phi(-d_1). \end{aligned}$$

Here K is the strike and τ is the term to maturity and r_τ is applicable interest rate over the period. $\Phi(\cdot)$ denotes the cumulative normal distribution and

$$\begin{aligned} d_1 &= \frac{\ln \frac{S_t}{K} + (r_\tau + \frac{1}{2}\sigma^2)\tau}{\sigma\sqrt{\tau}}, \\ d_2 &= d_1 - \sigma\sqrt{\tau}. \end{aligned}$$

Implicit in the option prices is the risk-neutral distribution (RND). In a dynamically complete market, the RND can be recovered from a set of European option prices using the relationship discovered by Ross (1976) and Breeden & Litzenberger (1978): The RND is proportional to the second derivative of the call or put option with respect to strike. In the ideal situation in which we have a continuum of option prices from zero to infinity, the RND could be uniquely and easily determined. In a dynamically complete market with no arbitrage opportunities, the time t price of the option Z_t can be found using risk-neutral valuation: the option price is expected present value of the future payoff under the risk-neutral measure. Therefore

$$\begin{aligned} Z_t &= \frac{1}{R_{t,T}} \mathbb{E}_t^Q \left[Z(S_T) \right] \\ &= \frac{1}{R_{t,T}} \int_0^\infty Z(S_T) f_t(S_T) dS_T, \end{aligned}$$

where

$$R_{t,T} := e^{\int_t^T r_\tau d\tau},$$

and $f_t(S_T) = f(S_T, T; S_t, t)$ denotes the risk-neutral transition probability under the probability measure $\mathbb{Q}$. This can be thought of as the probability of attaining a level of S_T at time T, given S_t at time t. Here r_t is the risk-free rate. Working with a forward price for simplicity, adjust both S_t and Z_t with the risk-free rate and the asset for dividends:

$$\begin{aligned} s_t &:= \frac{R_{t,T}}{D_{t,T}} S_t, \\ z_t &:= R_{t,T} Z_t, \end{aligned}$$

where

$$D_{t,T} := e^{\int_t^T \delta_\tau d\tau}.$$

Thus, s_t and z_t are the asset and option date-T forward prices and δ_t is the asset's instantaneous dividend yield at time t. In particular, forward prices for a European call $c_t(x)$ and put $p_t(x)$ with strike x are given as

$$\begin{aligned} c_t(x) &= \int_0^\infty \max(s_T - x, 0) f_t(s_T) ds_T, \\ p_t(x) &= \int_0^\infty \max(x - s_T, 0) f_t(s_T) ds_T \end{aligned}$$

where $s_T = S_T$. Forward put–call parity is then

$$p_t(x) + s_t = x + c_t(x).$$

The current prices have been adjusted by $D_{t,T}$. Differentiating $c_t(x)$ and $p_t(x)$ twice with respect to strike (evaluated at $x = s_T$) yields the key to using options as a means to obtain the RND:

$$\begin{aligned} f_t(s_T) &= \left.\frac{\partial^2 c_t(x)}{\partial x^2}\right|_{x=s_T} \\ &= \left.\frac{\partial^2 p_t(x)}{\partial x^2}\right|_{x=s_T}. \end{aligned}$$

Puts are usually more liquid than calls thus all references to the above will use $p_t(x)$. In the Black–Scholes model, the underlying is assumed to follow a lognormal distribution with constant variance. In this instance, a closed-form solution for the RND permits the price of any option to be easily computed. One requires a cross-section of options with common maturity T to estimate the RND of the underlying.

3.3.3 Positive Convolution Approximation (PCA)

The fully non-parametric method of Bondarenko (2003) is applied to the cross-section of European options to extract the probabilities (investors' beliefs) associated with the underlying ending in a particular interval at maturity; these values (y-axis) over the range of strikes (x-axis) gives rise to the RND. A set of admissible densities is constructed from which the optimal density (one that best fits option data) is selected. This set consists of all functions that can be represented as the convolution of a fixed kernel and some arbitrary density function. The choice of the kernel determines the 'smoothness' of the candidate densities.

The author justifies the use of nonparametric methods based on their flexibility, and reliance on the data. There are no strong assumptions made regarding the underlying (data generating) process. Alternative methods of this class are either implied tree methods (Derman & Kani 1994, Dupire 1994, Rubinstein 1994), or smoothing techniques. The latter rely on averaging observational errors in sophisticated ways. These methods are not generally suitable for ill-posed problems which may also involve noise or sparse data. This ultimately distorts genuine features of the function. There is also a trade-off between smoothness and fit, as the violation of arbitrage opportunities can lead to negative probabilities or the RND may not integrate to unity. These issues do not arise with PCA. Examining the performance of both parametric and non-parametric comparative estimators, the author shows that PCA outperforms the mixture of three lognormals, which is designated in the experiment as the correct parametric model. The method ensures that the no-arbitrage constraints are adhered to since the mean is equated to the asset's forward price in the computational program; only available data are used to construct the RND. This is therefore the choice of method applied based on the comparative performance.

Bondarenko (2000) applies the method to daily S&P 500 Index options (SPX) over the period 1991 to 1995 and finds that the implied RNDs exhibit negative skewness and excessive kurtosis (based on the robust moments defined in section 3.4). These departures from lognormality become more pronounced over time. The time series relation between the implied RND and the index return is also documented. It is shown that the shape changes in a systematic way, depending on whether the current index level is high or low: On trading days when the index declines, the implied RND is more skewed and peaked. The second moment is also negatively correlated with the index return. The interpretation is that investors' subjective probability density and/or risk preferences are time-varying and correlated with the index return. Thus, when the index declines, investors become more pessimistic about future returns and more risk averse. This leads to a RND with fatter tails. When the index performs well, investors become optimistic and the RND is less skewed and closer to the historical density.

In order to calculate the RND for a given trading date, the function requires the following inputs:

- A vector of all OTM put option prices, $P_{t,T}(K_i)$. Given the prevalence of these options, forward put–call parity is applied to the ITM call options to infer OTM put option prices.
- A vector of the corresponding strikes, K_i.
- The ATM implied futures level, $F_{t,T}$.
- The ATM implied volatility, $\sigma_{t,T}^{ATM}$
- A range over which the RND probabilities are to be calculated. This ideally reflects the range of strikes available.

The means to obtain all these input variables is described in section 3.5.2.

3.4 Option-Implied Sentiment Measures

3.4.1 The At-the-Money Implied Cumulative Probability $p_{t,T}^{RND}$

The RND which is inferred from European index options is given as the y-values of $y = f(S_T)$, a function which maps the asset price space at maturity T, S_T to probabilities $f(S_T)$ such that the sum integrates to unity, as is required of a density function. The PCA applies the no-arbitrage constraint to ensure $S_T = s_t$. By evaluating the probability mass to the left of the mean on a daily basis, one can see the shift in probability mass across the mean s_t; this is then assumed to be tantamount to a shift in investor sentiment. Increased bullishness implies a greater probability associated with the index exceeding the current ATM futures level. This is subject to the empirical derivation of the RND. The specification is particularly sensitive to the parameter choice required for the approximating grid of the x-axis (asset price at maturity). Regardless, the T-day forward-looking cumulative probability $p_{t,T}^{RND}$, where $T = 30$ in the empirical analysis, is considered a bearish measure. As more mass accumulates to the left of the mean, investors' demand for index put options tends to increase in line with their prices and associated implied volatilities. A decrease in the implies skew is thereby expected. Specifically,

$$\begin{aligned} p_{t,T}^{RND} &= \sum_{i=1}^{i^*} f(x_T^i), \\ x_T^{i^*} &= s_t. \end{aligned}$$

3.4.2 The Third Robust Moment $\eta_{t,T}^3$

This measure of the skew is unique to the method employed to extract the RND. The time series relationship pertaining to contemporaneous and lagged daily index returns has been established: Bondarenko (2000) finds the returns to be positively related to $\eta_{t,T}^3$, regardless of T. When the index advances, $\eta_{t,T}^3$ became less negative. Since the RND is determined by investors' subjective probability of the asset's future returns as well as their risk preferences, investors' beliefs as well as attitude towards risk may vary in response to the recent index movement. Thus, decreases in the index may induce a more bearish market and investors' may become more risk averse in the near future. This may in turn warrant enhanced portfolio insurance which leads to fatter left tails of the RND. To the contrary, recent good performance may result in less risk aversion and a higher degree of optimism. Hence, $\eta^3_{t,T}$ is expected to increase (less negative) and so too a shift in mass to the right of the mean is expected.

Due to missing option data required for the tails of the distribution, to reliably estimate the higher moments is subject to scepticism (variance, skewness, kurtosis). Thus, to overcome the deficiency of data to construct the tails, Bondarenko proposes the 'robust' moments approach, which is defined in terms of percentiles. The distribution for the underlying at maturity T, $f(S_T)$ is converted into the associated returns distribution $g(u_T)$ where $u_T = \ln \frac{S_T}{s_t}$[14] using the change of variables method[15]. Since we have that $S_T = s_t e^{u_T}$, it then follows that $g(u_T) = f(S_T e^{u_T}) S_T e^{u_T}$.

Let U_n denote the nth percentile of $g(u_T)$. The percentile of the return distribution can be found by finding the x-value which corresponds to the nth percentile of the cumulative density function (CDF). Once $g(u_T)$ has been found, the CDF is given by $\mathbb{P}[u_T \leq X] = \Sigma_{i=1}^{i=k} g(u_T^i) du_T^i$, where k represents the number of points on the approximating grid such that $X = \ln \frac{S_T^k}{s_t}$ and $du_T = \frac{d}{dS_T}\left(\ln \frac{S_T}{s_t}\right) dS_T = \frac{dS_T}{S_T}$. It can be shown that $g(U_T)$ is in fact a probability density function since

$$\begin{aligned}\int_{-\infty}^{\infty} g(u_T) du_T &= \int_{-\infty}^{\infty} f(s_t e^{u_T}) s_t e^{u_T} \frac{dS_T}{S_T} \\ &= \int_{-\infty}^{\infty} f(S_T) dS_T \\ &= 1.\end{aligned}$$

Thus, U_{50} is the median of the return distribution. For the distributions which include U_{10} and U_{90}, the first four annualised robust moments are defined as follows:

$$\begin{aligned}\eta^1_{t,T} &= \frac{1}{\tau}\left(U_{50} + \frac{1}{2}\left(\eta^2_{t,T}\right)^2 \tau\right), \\ \eta^2_{t,T} &= \frac{1}{\sqrt{\tau}} \frac{U_{90} - U_{10}}{2.5631}, \\ \eta^3_{t,T} &= \frac{(U_{90} - U_{50}) - (U_{50} - U_{10})}{U_{90} - U_{10}}, \\ \eta^4_{t,T} &= 0.4092 - \frac{U_{70} - U_{30}}{U_{90} - U_{10}}.\end{aligned} \tag{3.1}$$

[14]At this point in the RND evaluation, the futures level $F_{t,T}$ has calculated as explained in section 3.5.2 and therefore, $s_t = F_{t,T}$ here.

[15]The *change of variables* approach for a probability density function (pdf) f_X is applied when it is required to find the pdf of $Y = h(X)$ such that $f_{h(X)} = f_X$. Since $|f_Y(y)dy| = |f_X(x)dx|$, we then have that $f_Y(y) = \left|\frac{dx}{dy}\right| f_X(x) = \left|\frac{1}{h'(h^{-1}(y))}\right| f_X(h^{-1}(y))$.

Here, $\tau = \frac{T-t}{365}$. Bondarenko justifies the definitions above given that the log-return RND for the Black–Scholes model is normal, $g(u) = \phi_{\sigma\sqrt{\tau}}\left(u + \frac{1}{2}\sigma^2\tau\right)$, where $\phi(\cdot)$ refers to the normal density function and $\Phi(\cdot)$ is the normal cumulative distribution function. The robust moments for this distribution are all zero. In order to normalise $\eta^2_{t,T}$, the interdecile spread is divided by $\Phi(90) - \Phi(10) = 2.5631$ and $\sqrt{\tau}$ to compare different maturities. The adjustment of $\frac{1}{2}\left(\eta^2_{t,T}\right)^2\tau$ to $\eta^1_{t,T}$ is applied as the Black–Scholes distribution $g(u)$ is centred at $\frac{1}{2}\sigma^2\tau$, not zero. $\eta^3_{t,T}$ takes values in the range $[-1, 1]$, and measures how the median of the distribution is located, relative to the extreme deciles. The fourth moment measures the excess peakedness. The constant 0.4092 is selected to ensure that for a normal distribution, it equates to zero. The third and fourth moments are relative measures and therefore, do not require annualisation. The author notes that robust moments may be less useful than standard moments for extreme events, given that we are using the 10th and 90th percentiles.

Bondarenko finds that as the index advances, the first, second and fourth moments decrease whilst the third increases (became less negative). As the asset price declines, the investors may become more pessimistic about future asset returns as well as more risk averse. Both effects contribute to fatter left tails. After increases in the index, investors become more optimistic and less risk averse. The resultant impact on $p^{RND}_{t,T}$ is unclear at first blush. If $U_{50} - U_{10}$ increases ($U_{90} - U_{50}$ decreases), then $\eta^3_{t,T}$ becomes more negative. The probability $p^{RND}_{t,T} = \mathbb{P}[S_T \leq s_t]$, where $U_{10} < p^{RND}_{t,T} \leq U_{50}$ may either increase or decrease. What may also occur is the narrowing or widening of the RND. The denominator may alter, thereby increasing or decreasing this moment. This will be established and explained in subsequent sections.

3.4.3 The BKM Model-Free Risk-Neutral Skew

In order to ensure that the time series properties of the robust moments are consistent, the risk-neutral skewness measure of BKM will be used. This is a model-free measure which does not require any assumptions regarding state variables or the functional form of the RND. Henceforth, this measure will be identified by MFIS (model-free implied skewness). It is an ex ante measure of the conditional skewness of the index return as it is inferred from option prices which account for investors' expectations of the future level of the index. Bakshi, Kapadia & Madan (2000) demonstrate that any payoff function with bounded expectations can be spanned by a continuum of OTM puts and calls. Thus, the prices of the payoffs can be expressed as a linear combination of such options. Skewness can be expressed as a function of the current prices of the quadratic, cubic and quartic continuously compounded return of the underlying asset. Expressing these payoffs as a linear combination of OTM options, the skewness can then be expressed as a function of current observed option prices. As before, $R_{t,T} = \ln\left(\frac{S_T}{S_t}\right)$ denote the continuously compounded return of the asset at time $T = t + \tau$, then the payoffs under the risk-neutral measure at time t can be expressed as

$$
\begin{aligned}
V_{t,T} &\equiv \mathbb{E}_t^Q\left[e^{-r\tau}R_{t,T}^2\right], \\
W_{t,T} &\equiv \mathbb{E}_t^Q\left[e^{-r\tau}R_{t,T}^3\right], \\
X_{t,T} &\equiv \mathbb{E}_t^Q\left[e^{-r\tau}R_{t,T}^4\right].
\end{aligned}
$$

Using only OTM European options with non-zero volume on those trading dates, the risk-neutral skewness for trading date t of the RND of the index return over the period $[t, T]$ can be obtained using the following:

$$
\mathrm{MFIS}_{t,T} = \frac{e^{r\tau}W_{t,T} - 3\mu(t,\tau)e^{r\tau}V_{t,T} + 2\mu_{t,T}^3}{\left[e^{r\tau}V_{t,T} - \mu_{t,T}^2\right]^{3/2}}, \tag{3.2}
$$

$$
\begin{aligned}
\mu_{t,T} &= \mathbb{E}_t^Q\left[\ln\left(\frac{S_T}{S_t}\right)\right] \\
&\approx e^{r\tau} - 1 - \frac{e^{r\tau}}{2}V_{t,T} - \frac{e^{r\tau}}{6}W_{t,T} - \frac{e^{r\tau}}{24}X_{t,T}.
\end{aligned} \tag{3.3}
$$

Here, $V_{t,T}$, $W_{t,T}$ and $X_{t,T}$ are weighted sums of OTM European call prices $C_{t,T}(K)$ and put prices $P_{t,T}(K)$ with time to expiry T and strike K, given the current underlying index price S_t:

$$
\begin{aligned}
V_{t,T} &= \int_{S_t}^{\infty} \frac{2\left(1 - \ln\left(\frac{K}{S_t}\right)\right)}{K^2} C_{t,T}(K)dK + \int_0^{S_t} \frac{2\left(1 + \ln\left(\frac{K}{S_t}\right)\right)}{K^2} P_{t,T}(K)dK, \\
W_{t,T} &= \int_{S_t}^{\infty} \frac{6\ln\left(\frac{K}{S_t}\right) - 3\left[\ln\left(\frac{K}{S_t}\right)\right]^2}{K^2} C_{t,T}(K)dK - \int_0^{S_t} \frac{6\ln\left(\frac{K}{S_t}\right) + 3\left[\ln\left(\frac{K}{S_t}\right)\right]^2}{K^2} P_{t,T}(K)dK, \\
X_{t,T} &= \int_{S_t}^{\infty} \frac{12\left[\ln\left(\frac{K}{S_t}\right)\right]^2 - 4\left[\ln\left(\frac{K}{S_t}\right)\right]^3}{K^2} C_{t,T}(K)dK \\
&\quad + \int_0^{S_t} \frac{12\left[\ln\left(\frac{K}{S_t}\right)\right]^2 + 4\left[\ln\left(\frac{K}{S_t}\right)\right]^3}{K^2} P_{t,T}(K)dK.
\end{aligned}
$$

Dennis & Mayhew (2002) have used this method, applying a trapezoidal approximation to estimate the integrals. The two sources of bias may be derived from discreteness in strikes and asymmetry in the domain of integration. Using simulated option prices from the Black–Scholes model, they found the effects of this to be negligible.[16] The bias introduced from asymmetry was found to be significant (in the range of ± 0.1) but could be mitigated by using the largest range of strikes available such that the domain of integration is symmetric. Over the period 1986 to 1996, they found that the average skewness of the SPX options were more negative (–1.6) compared with that of the individual stock options (–0.24).

Bakshi et al. (2003) examine data between 1991 and 1995 looking at both individual equity options and that of the S&P 100 (OEX). They provide a theoretical characterisation that links the risk-neutral skew to risk aversion. They find that the more negatively skewed the return distribution, the steeper its volatility smile. However, the more fat-tailed the return distribution, the less the smile is downward sloping. Thus, a higher kurtosis flattens the smile in the presence of left tails. The differences in the skews of the risk-neutral and physical distributions are attributed to risk aversion.

Hansis, Schlag & Vilkov (2010) have proposed applying a spline interpolation to implied volatilities, prior to using the option prices. Specifically, since a continuum of option prices are required to calculate the integrals, a cubic spline is used to interpolate implied volatilities within the available moneyness range. Outside this range, implied volatilities are extrapolated using the boundary values to fill 1001 grid points in the moneyness range from 1/3 to 3. Using the risk-free interest rate, the option prices are then calculated based on the interpolated implied volatilities for a given maturity. This is the method that will be used here as it has been shown to reduce the bias considerably. Furthermore, the authors suggest the enhancement may invalidate previous results which apply a trapezoidal method to the coarse grid of available option data.

3.4.4 The XZZ Smirk

There is a one-to-one mapping between skewness and the slope of the implied volatility smile/smirk. Negatively sloped curves (higher volatilities are observed for OTM put options than in-the-money (ITM) put options) correspond to negative skewness in the risk-neutral density function. Bakshi

[16] Skewness is zero in the Black–Scholes model. Using an interval of \$5 and \$2.5, they found the bias that was introduced was roughly –0.07 and –0.05 respectively.

et al. (2003) find a high correlation between their skewness measure and the slope of the implied volatility curve. The last measure pertaining to the distribution that will be examined is the volatility smirk of Xing et al. (2008). This is defined as

$$\sigma_{t,T}^{smirk} = \sigma_{t,T}^{OTMp} - \sigma_{t,T}^{ATMc},$$

where $\sigma_{t,T}^{OTMp}$ refers to an OTM put options and $\sigma_{t,T}^{ATMc}$ refers to an ATM call option at date t for an option with maturity T. A put option is defined at being OTM when the ratio of strike price to stock price lies in the range (0.8 0.95), and a call option is ATM when the ratio of strike price to stock price lies in the range (0.95 1.05). The skew is averaged over a week in the authors' research, however for purposes of a daily sentiment measure, we look at daily skew for the index. In the instance that there are multiple options which satisfy this range, the final implied volatility is a volume-weighted average over all relevant implied volatilities.

3.4.5 The Put–Call Option Volume Ratio

For each day the RND is extracted, the volume of index puts to index calls can be measured. Analogously to the CBOE put–call ratio mentioned in section 3.2.2, the ratio here is define exclusively for SPX options. The two measures $PCR_{t,T}$ and $ModPCR_{t,T}$ are defined with reference to the volume of SPX call and put options for a specific maturity T, $C_{t,T}^V$ and $P_{t,T}^V$:

$$\begin{aligned} PCR_{t,T} &= \frac{\sum_i P_{t,T}^V}{\sum_j C_{t,T}^V}, \\ ModPCR_{t,T} &= \frac{\sum_i P_{t,T}^V \mathbf{1}_{OTM}}{\sum_j C_{t,T}^V \mathbf{1}_{OTM}}. \end{aligned}$$

The modification in the second instance is more stringent as the requirement is to limit each sum to the OTM options as opposed to all options, thereby capturing extreme opinions. This measure is expected to be greater than unity given that portfolio insurance is likely to tilt the volume towards put options.

3.5 Empirical Section

This section describes the data required to extract the RND and therefore, the calculate $p_{t,T}^{RND}$, $\eta_{t,T}^3$, the BKM $MFIS_{t,T}$, $\sigma_{t,T}^{smirk}$, $PCR_{t,T}$ and $ModPCR_{t,T}$. Henceforth, T refers to the 30-day measure and the subscript will be dropped. This data are to be examined daily. Weekly results incorporates the use of the II Survey: the bull–bear spread BB_t^S is the difference between bullish and bearish investor sentiment of a given week. The RND is extracted in Matlab; regression results are obtained using EViews.

3.5.1 Data

The following data are used for the period 3 January 2005 to 29 October 2010.

SPX Option Data

Daily SPX index option data are from Option Metrics, Wharton Research Data Services. As mentioned in section 3.3.3, to calculate the RND on a given date, the function requires input parameters: a vector of put option prices $\mathbf{P}_t$, the corresponding vector of strikes $\mathbf{K}_i$, the ATM futures level s_t, σ_t^{ATM} and a vector to represent the grid over which the RND is to be estimated. In order to calculate p_t^{RND}, η_t^3, BKM $MFIS_t$, σ_t^{smirk}, PCR_t and $ModPCR_t$, the following are required for each trading date t: maturity, strike price, index close, dividend yield, put–call identifier, best bid, best offer, option volume, open interest, implied volatility and the delta of the option. The data are processed according to the method outlined in Bondarenko (2003); in the instance of the BKM $MFIS_t$, the data is adjusted according to Rehman & Vilkov (2010). Further clarification is in section 3.5.2.

Risk-Free Rate

The daily zero coupon yield curve is obtained from Option Metrics, Wharton Research Data Services. The appropriate risk-free rate for the option maturity is interpolated.

VIX

The daily VIX is from CBOE Indices, Wharton Research Data Services.

Bull–Bear Spread BB_t^S

The weekly Advisors Sentiment bullish and bearish survey index over the period is from Thomson Datastream. The data is released on Tuesdays. Key identifiers are USIIBUL (bullish sentiment) and USIIBER (bearish sentiment).

3.5.2 Option Data Restrictions

Noisy data can pose an issue of over-fitted or irregular estimators for the second derivative. A solution to this is to impose the estimator to be a 'smooth' function which reliably estimates the data. This achieves better stability for the RND function. To ensure that the RND satisfies the no-arbitrage conditions – a non-negative function which integrates to unity – many methods modify the estimator. For any given maturity, there are usually more options traded below the current spot level than above, implying that options contain more information about the left tail than the right. OTM options are more liquid than ITM options and puts are more liquid than calls. In practice, there are various limitations to this process:

- Very low and high strikes are usually unavailable, which then implies there is little information known about the tails. Thus it is impossible to calculate higher moments of the distribution.
- The problem of calculating the function's second derivative is ill-posed as prices are observed with noise (nonsynchronous/stale trading of options, price discreteness and bid–ask bounce);
- Prices are observed for a discrete set of strikes (\$5 apart for the near-term and \$25 for the longer-term SPX options).

Exchange rules dictate that new strikes are added to span the vicinity of the current price of the underlying. Data are usually unavailable for the tails of the RND; this then means that it cannot be reliably estimated, even over the range of strikes. Thus, if x_l and x_h denote the lowest and highest strikes available then the RND cannot contain much more information in the tails above and below these strikes. Options with longer maturities usually have less available information in the tails. Many methods assume that the entire range of strikes is available. The tails are often assumed to be lognormal or require an extrapolation mechanism of sorts. The RND tails become a result of the assumptions used to generate them and are not a feature of the underlying data. The RND estimation over the available strikes may also be sensitive to the method chosen to parametrise the tails.

When applying PCA, one of the inputs is a grid of x-values which represents the possible terminal values for the underlying asset. The grid need not be equally spaced and is selected to span the entire range of option strikes and ensure the CDF equates to unity. In the empirical results, the lower bound is $x_l = K_l - 300$, and upper bound $x_h = K_h + 100$; K_l and K_h are the lowest and highest available strikes respectively. A spacing of \$5 is selected for both near-term and longer-term maturities in line with the available strikes. When calculating η_t^3, the transformation from linear space in the variable S_T to the natural logarithm space of u_T is required.

The following exclusion filters are applied to the data when calculating the RND to avoid any micro-structure related bias:

- Eliminate options with zero trading volume and prices below 1/8 (this is the average of the bid and ask);
- Eliminate options with extreme far-from-the-money strikes if they are separated from the main group of strikes: The lowest and highest strikes are eliminated if the next closest available strikes are 25 (40) points or more away for near-term (longer-term) maturity groups. The near-term options correspond to the first three months, all options thereafter are considered longer-term maturities.
- Eliminate all options with maturities of seven days or less.

The following steps are employed to clean the options to reduce the impact of real-world imperfections due to nonsynchronous trading, bid–ask bounce and discreteness of option prices:

- The RND is estimated using put options as they are more liquid than calls. To exploit the more liquid OTM options, forward put option prices $\bar{p}_t(K)$ (notation refers to the price being inferred) are inferred from the forward OTM calls using the put–call parity relationship, for each strike K_i:

$$\bar{p}_t(K_i) \quad := \quad K + c_t(K_i) - s_t.$$

Forward option prices are calculated by multiplying the option price by $e^{r_\tau \tau}$ where r_τ refers to the risk-free rate calculated from Treasury bills which is applicable over the period τ, and $\tau = \frac{(T-t)}{365}$. This reduces the issue of nonsynchronous trading. Thinly traded ITM puts (which are rarely traded and have higher bid–ask spreads and are more susceptible to changes in the underlying asset since delta is close to 1) are replaced using the more liquid OTM call options. The ATM futures level $F_{t,T} = s_t$ is required to calculate this relation. These prices are to be inferred from pairs of actively traded ATM options to avoid imperfect synchronisation. For the closest to the ATM strikes K_{ATM}, $p_t(K_{ATM})$ is replaced with the average of $p_t(K_{ATM})$ and $\bar{p}_t(K_{ATM})$.

- To obtain the ATM futures level s_t,[17] consider several of the closest to the ATM strikes K_{ATM} such that $|s_t - K_{ATM}| < 15$ for near-term maturities or $|s_t - K_{ATM}| < 25$ for longer-term maturities. For those strikes which have both call and put option data available, the average is then taken to obtain the futures level $s_t = c_t(K_{ATM}) + K_{ATM} - p_t(K_{ATM})$.
- The forward put prices should satisfy the no-arbitrage restrictions:
  - Forward put price $p_t(K_i)$ is a convex function of strike K_i;
  - $0 \leq \frac{\partial p_t(K)}{\partial K} \leq 1$ for all strikes K_i.

A daily cross-section is discarded if either there are less than 10 options available with which to estimate the RND or if substantial violations of the no-arbitrage conditions are detected (if the square root of the average squared deviation of put prices from the closest arbitrage-free prices is greater than 0.4).

In order to calculate the T_{30} 30-day measures for all variables selected, the RNDs for maturities preceding and succeeding T_{30} are first estimated. For each date t, the maturity dates T_1 and T_2 are selected such that $T_1 \leq T_{30} \leq T_2$. Daily data for the five trading days are calculated using the available maturities which satisfy all the constraints. In the instance that the first viable

[17] The ATM futures level is henceforth denoted s_t.

maturity T_m closest to T_{30} satisfies the relation $T_m > T_{30}$, this will be used as an approximation for T_{30}. Daily data yields a daily sentiment measure for institutional investors which adjusts according to portfolio insurance requirements; this is implicit in the probability measure and skew-related measures. Once all daily inputs are available, the PCA method can be applied. All Matlab code has been written in accordance with these guidelines with the exclusion of the PCA function required to evaluate the RND, which is written by Bondarenko (2003).

When calculating the BKM $MFIS_t$, the restrictions outlined in Rehman & Vilkov (2010) are adhered to. The Matlab code provided by the source [18] is used in this implementation. The following options are removed before implied volatilities and the $MFIS_t$ is calculated:

- Options with zero bids;
- Options with zero open interest – this is less stringent than removing options with zero volume however does leave more data available for calculations, regardless of the possibility of using stale data;
- Options with maturity less than 14 days;
- Options with maturity longer than 200 days;
- Options which have a moneyness less than 0.7 or greater than 1.3;
- Given that only OTM options are required, options with deltas less than 0.5 or greater than 0.5 are excluded; [19]
- Options which have a price (average of the best bid and best offer) less than 0.5.

Verification of the methods is achieved through their application to call and put options that are priced using the Black–Scholes formula with constant volatility parameter. Applying the PCA method for a given trading date t, the RNDs for the a range of expiries available can be extracted. In Figure 3.1 the current date is 15 January 2010 and the expiries are as shown. As previously mentioned, it is clear that as maturities extend further into the future, the RND displays fatter tails and are less-peaked, indicating greater uncertainty.

[18] `http://vilkov.net/www/content/code-and-useful-stuff`

[19] Call options have a delta between [0 1]; put options have a delta between [–1 0]. Thus, when call (put) options are ITM, their delta approaches 1 (–1).

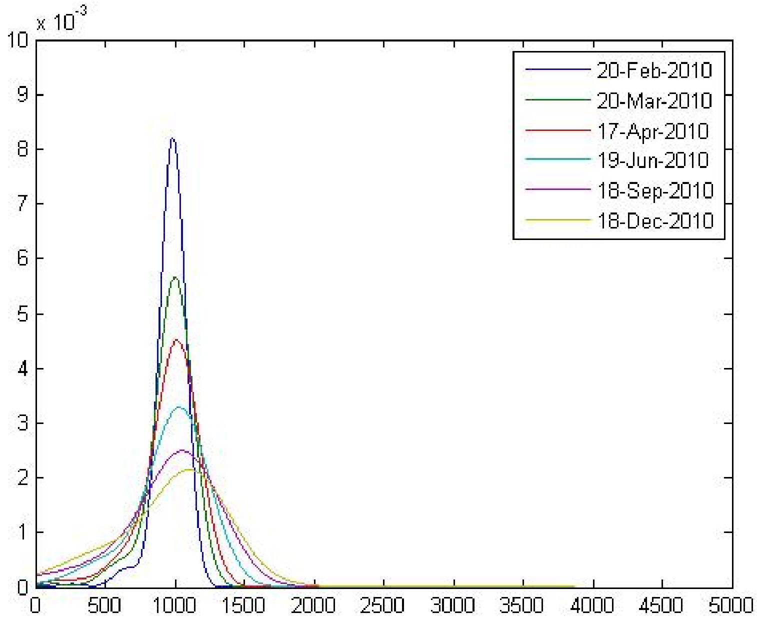

Figure 3.1: The S&P 500 index RNDs on 15 January 2010 for maturities listed where the index value (x-axis) is plotted against the corresponding probability (y-axis). The \$5 spacing is applied which then renders the area under the graph equal to one.

Figure 3.2 displays the evolution of the RND over a given number of dates listed below for the option maturity 20 February 2010; axes are as in Figure 3.1.

3.5.3 Daily Time Series Properties of $p_{t,30}^{RND}$

Given that daily data between 2005 and 2010 are used within the analysis, evidence of the subprime crisis is likely to be detected. Relationships that may exist between variables in times of normal market conditions may not be evident during market turmoil. The time line of the crisis [20] mentions that concerns about the subprime market arose during June 2007 when the Dow industrials plunged 198.94 points and the yield on 10-year Treasury notes rose to 5.10% amid inflation concerns. The analysis will be carried out over three periods: the entire period, the pre-crisis period (January 2005 to end of June 2007) and then post-crisis period (July 2007 to October 2010).

The mean value of the series $p_{t,30}^{RND}$ which corresponds to the probability of the index reaching the ATM futures level in 30 calendar days is $\mu = 0.44$, and standard deviation is $\sigma = 0.02$. Given

[20] `http://online.wsj.com/article/SB120576387418941803.html`

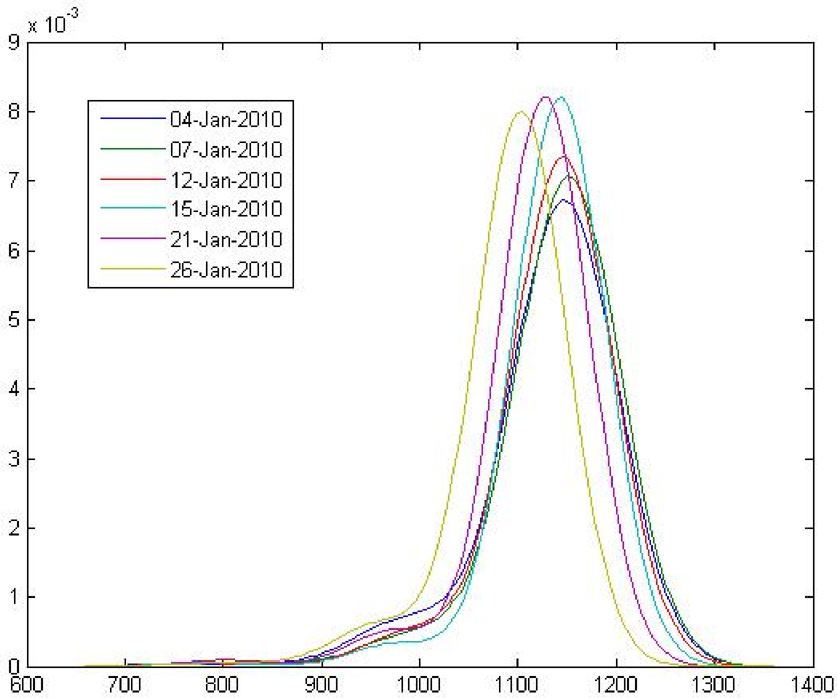

Figure 3.2: The evolution of the S&P 500 index RND from options with expiry 20 February 2010. Once again, a \$5 spacing is applied.

that the RND is constructed to ensure that the mean equates to s_t, this is expected. The series exceeds the range $\mu + 3\sigma$ in November 2007 and February 2009, and dips below $\mu - 3\sigma$ during August of 2007.

For daily data from 3 January 2005 to 29 October 2010, the $p_{t,30}^{RND}$ is autoregressive, and therefore one lag will be included in all regressions to control for positive autocorrelation. The residuals of the time series, labeled ϵ_t, follow an ARMA(1,1) process. The model which appears to best fit the data is then

$$p_{t,30}^{RND} \quad = \quad \alpha + \beta p_{t-1,30}^{RND} + \epsilon_t, \tag{3.4}$$

where ϵ_t is an ARMA(1,1) process. Results are in Table 3.1 for daily data over the entire period. The Durbin–Watson statistic (a test for first-order serial correlation of residuals) [21] is only applicable when the dependent variable is not on the right-hand side of the equation. For errors which are AR models, the residual-based regression statistics reported are based on the

[21] A statistic below 2 indicates positive serial correlation whilst that between 2 and 4 indicates negative correlation.

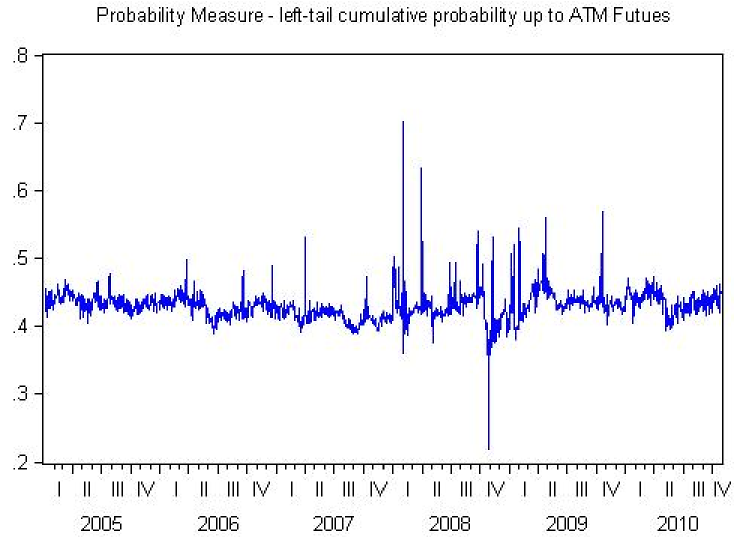

Figure 3.3: The daily 30-day probability measure $p_{t,30}^{RND}$ over the sample period. The is the cumulative probability of the index attaining the ATM futures level 30 calender days hence.

Table 3.1: Daily regression results estimated for the $p_{t,30}^{RND}$ over the period 3 January 2005 to 29 October 2010, estimated using equation (3.4)

Variable	Coefficient		Std. error	t-statistic	Prob.
α	0.0062		0.0019	3.2871	0.0010
$p_{t-1,30}^{RND}$	0.9860		0.0043	231.8230	0
AR(1)	0.3890		0.0287	13.5630	0
MA(1)	–0.8650		0.0181	–47.7819	0
R-squared	0.6620	Mean dependent var			0.4431
Adjusted R-squared	0.6615	S.D. dependent var			0.020
F-statistic	1383.776	Durbin–Watson stat			2.0412
Prob(F-statistic)	0				
Inverted AR roots	0.39				
Inverted MA roots	0.86				

one-period ahead forecast errors. [22] In all tabulated regression results, the 'variable' column refers to the coefficient of that listed with the exclusion of the constant α.

The coefficient of $p_{t-1,30}^{RND}$ is close to unity due to the frequency of data; both $p_{t,30}^{RND}$ its residuals ϵ_t are autocorrelated. The null hypothesis of the presence of a unit root is rejected at the 1%

[22]These residuals represent the forecast errors one would make if one computed forecasts using a prediction of the residuals based upon past values of the data, in addition to the contemporaneous information. In essence, there is an improvement upon the unconditional forecasts and residuals by taking advantage of the predictive power of the lagged residuals.

critical level using the ADF test.

A brief digression to monthly data reveals how $p_{t,30}^{RND}$ shifts in response to movements in the underlying index. The monthly $p_{t,30}^{RND}$ data (both an average of all business day observations and the end-of-month value which is the last business day observation for that month) are estimated as a comparison; Figure 3.4 displays how remarkably different the final time series appear. The probability appears to be declining up to the mid-2007 crisis after which it steadily increases, conceivably as a result of the demand for portfolio insurance increased. Granger causality with two lags between the monthly index close and the average $p_{t,30}^{RND}$ over the month shows causality running from the index close to $p_{t,30}^{RND}$ (F-statistic 5.04, p-value 0.01). The monthly correlation between the index and $p_{t,30}^{RND}$ is –0.46. This therefore implies that contemporaneous increases in the index lead to an increase in investor sentiment as the $p_{t,30}^{RND}$ decreases. That is, investors perceive there to be a greater probability of the index exceeding the ATM futures level.

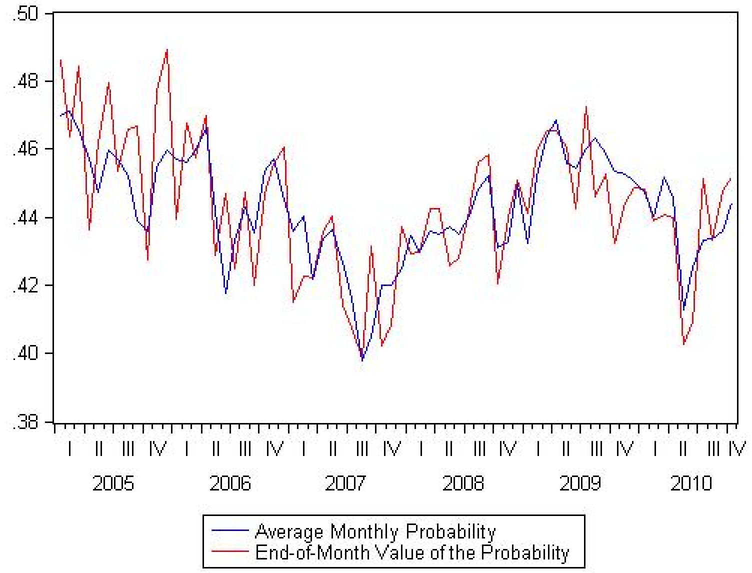

Figure 3.4: The monthly probability measure $p_{t,30}^{RND}$ for the period January 2005 to October 2010, both an average of all business day observations and the end-of-month value.

Henceforth, the 30-day subscript will be dropped and the assumption is such that for all variables $x_{t,30} = x_t$. Ensuring multicollinearity of daily data is avoided, the correlations of the variables p_t^{RND}, η_t^3, $ModPCR_t$, PCR_t, $MFIS_t$, σ_t^{smirk} and the VIX are estimated. The entire daily sample period has been divided into two parts for robustness checks as well as to identify normal and

Table 3.2: Daily correlations of sentiment variables examined for the entire period, followed by the pre-crisis and post-crisis periods respectively.

Correlation	p_t^{RND}	η_t^3	$ModPCR_t$	PCR_t	$MFIS_t$	σ_t^{smirk}	VIX
p_t^{RND}	1						
η_t^3	0.6674	1					
	0.6098	1					
	0.7364						
$ModPCR_t$	0.0252	0.0109	1				
	0.02570	0.0376					
	0.0368	0.0319					
PCR_t	–0.0156	–0.0455	0.9269	1			
	–0.0827	–0.0321	0.8010				
	0.0123	–0.0150	0.9463				
$MFIS_t$	0.2042	–0.2390	-0.0490	0.0067	1		
	0.3473	0.1883	–0.0442	0.0007			
	0.2437	–0.2311	–0.0745	–0.0200			
σ_t^{smirk}	-0.2282	–0.1634	0.0701	0.0965	–0.3785	1	
	–0.2418	–0.2424	–0.0018	0.0400	–0.4428		
	–0.1761	0.0235	0.0799	0.0951	–0.5384		
VIX	–0.0701	–0.515	–0.0416	0.0264	0.4372	0.2233	1
	-0.4009	–0.5748	–0.1235	0.0809	–0.1682	0.4172	
	0.1467	–0.2689	–0.0818	–0.0204	0.4248	0.0798	

crisis regimes: The pre-crisis (3 January 2005 to 30 June 2007) and post-crisis (1 July 2007 to 29 October 2010). The first value for each variable corresponds to the entire period, the second to the pre-crisis period and the third is the remainder of the time period.

Examining the results of Table 3.2, the sign alternates for both the VIX and the PCR during the different market conditions. PCR_t has been calculated by dividing all index puts by all index calls for a particular maturity, after the data have been cleaned. The T_{30} value is then interpolated from the relevant maturities. The correlation is insignificant in comparison to that of the VIX. The volatility index is a 30-day measure derived from SPX options. It tends to increase when the market experiences periods of fear, and when the market is on a bull run, albeit less so. From Figure 3.8, one can see that during the crisis period, the VIX starts to increase substantially. Hence, the negative sign during the pre-crisis period might imply that the VIX is increasing during positive momentum period however this causes a reduction in the probability measure as investors expect higher than average returns. During the crisis period when the market is less confident, an increase in the VIX tends to be accompanied by an increase in the probability. This can then be interpreted as a decline in the probability of exceeding

Table 3.3: Summary statistics for the variables over the period January 2005 to October 2010.

					Percentile		
Variable	Mean	Std. deviation	Max	Min	25	50	75
p_t^{RND}	0.4431	0.0203	0.5661	0.3755	0.4298	0.443	0.4569
η_t^3	–0.1787	0.0785	0.027	–0.4113	–0.2358	–0.1707	–0.1187
$ModPCR_t$	2.5956	2.4566	56.7071	0.2707	1.5741	2.1646	2.9557
PCR_t	2.1847	2.4507	62.415	0.3127	1.4126	1.8076	2.3863
$MFIS_t$	–1.7235	0.4251	–0.5664	–4.6322	–1.9847	–1.7227	–1.4113
σ_t^{smirk}	0.1013	0.0242	0.2947	–0.1008	0.0846	0.0992	0.1148
VIX	0.2176	0.1178	0.8086	0.0989	0.1291	0.1913	0.2548

the ATM futures level and therefore, a bearish sentiment. To further investigate this, the OLS regressions in the following sections provide insight to these relationships. All other variables exhibit the same linear relationships, regardless of the index movement. This will be explored further in section 3.5.5. Table 3.3 provides the summary statistics for the sentiment variables.

The following section primarily examines the relationship of BB_t^S with both p_t^{RND} and BKM $MFIS_t$ individually. This is to determine whether survey sentiment and that inferred from options data are congruent over different market regimes.

3.5.4 Weekly Results

Figure 3.5 displays the weekly data for the bull–bear spread, BB_t^S. The series has a mean of 0.16 and attains a maximum value of 0.42 and minimum of –0.32. The weeks during which the index exceeds 90% of the maximum value were 7 January 2005, 12 August 2005, 30 December 2005 and 19 October 2007. The corresponding minimum values occurred during the weeks of October 2008. The months in which the series was negative occurred during March 2008 and extended over 2008, with the exception of May, to the end of April 2009. Negative values were also recorded during July and September 2010.

In order to determine whether BB_t^S may be a result of past returns, a momentum variable captured by the six month log-return, $m_t = \ln \frac{S_t}{S_{t-180}}$ is defined. Graphically, the relationship can be seen in Figure 3.6. Granger causality using two lags is performed to establish direction of information flow. Results indicate momentum Granger-causes BB_t^S (F-statistic 14.79, p-value 0.00). The time series BB_t^S is autocorrelated with lag one, with errors that follow a AR(1) process (the constant is 0.01). Thus one lag will be included in all regressions that follow, correcting for

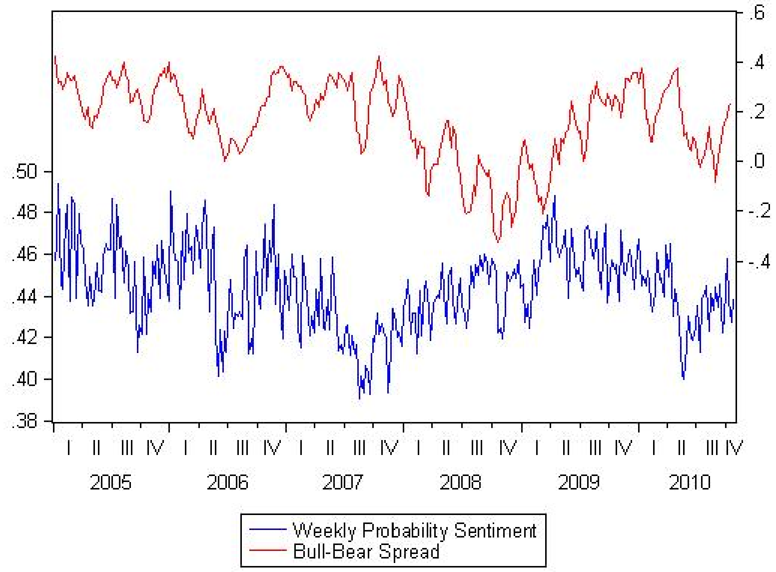

Figure 3.5: The weekly bull–bear spread (right axis) and probability measure p_t^{RND} (left axis) from January 2005 to October 2010.

serial correlation of errors. Examining the relationship between BB_t^S and the most recent one week log-return over the entire period, we find a positive constant ($\beta_2 = 0.56$) when looking at the AR(1) equation $BB_t^S = \alpha + \beta_1 BB_{t-1}^S + \beta_2 \ln \frac{S_t}{S_{t-1}} + \epsilon_t$, which is statistically significant (t-statistic of 4.27, p-value of 0, standard error is 0.13). Thus, institutional investor sentiment as measured by the bull–bear spread is related to past S&P 500 returns, as was discussed in Solt & Statman (1988) and Fisher & Statman (2000).

Table 3.4 contains the correlations of the bull–bear spread BB_t^S, p_t^{RND}, η_t^3, $ModPCR_t$, $MFIS_t$ and σ_t^{smirk} over the entire sample period, followed by the pre-crisis (2005 to mid-2007) and post-crisis (mid-2007 to 2010) periods. Examining the first column, it can be seen the signs of the variables p_t^{RND}, $MFIS_t$ and σ_t^{smirk} alternate in the sub-periods. Given that the BB_t^S is positive up to March 2008, one expects the correlations to change signs as trading in the options markets retains the same level of activity. The exception to this is η_t^3 which is shown below in Figure 3.7. The third robust moment is a measure of the distribution of weight in the density function of the returns distribution, as estimated using the PCA method. Hence this measure is closely related to p_t^{RND}: as the mass in the left-hand side of the distribution increases, from the definition of η_t^3, it is clear that this measure will be more negative as $U_{50} - U_{10} > U_{90} - U_{50}$, where U_x refers to the x-percentile of the returns distribution, assuming that the denominator is fixed. At a point in

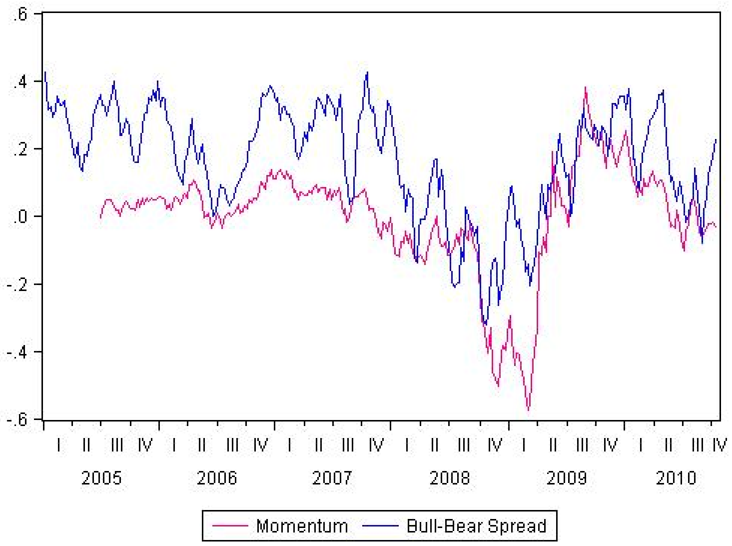

Figure 3.6: The weekly bull–bear spread from January 2005 to October 2010 graphed with the momentum variable m_t.

time which is fairly close to maturity, the distribution rarely changes width. p_t^{RND} is the mass in the CDF to the left of the mean of RND, up to a point s_t, which alters daily. This value is neither the theoretical forward nor is it determined from the futures market; it is determined from the options data as explained in section 3.4. The positive correlation implies that the more bullish the survey responses are, the less negative the third robust moment. The VIX is negatively correlated throughout which can be interpreted as follows: If the market is on a steady incline, the VIX will decrease and the bull–bear spread will then increase. Downward-trending markets result in fear and a subsequent increase in the VIX. The bull–bear spread therefore decreases as investors become bearish from recent poor market performance.

Regressions involving the PCR and modified PCR do not present any convincing relationships and therefore, the results are not displayed here. Dennis & Mayhew (2002) did not find any evidence that skewness was related to the PCR. Given that a low PCR may imply investors are bullish, this not need be the case; a high volume in call options may also be a result of call-selling activity that is bearish and the same can be concluded from the put-selling activity with regards to the market being bullish. This line of reasoning is likely to hold for single stock options. The

Table 3.4: The correlations of the weekly variables below, over the entire period, followed by the pre-crisis and post-crisis periods respectively.

Correlation	BB_t^S	p_t^{RND}	η_t^3	$ModPCR_t$	$MFIS_t$	σ_t^{smirk}	VIX_t
BB_t^S	1						
p_t^{RND}	0.0934	1					
	0.2954						
	–0.1098						
η_t^3	0.4929	0.6449	1				
	0.3532	0.5816					
	0.3517	0.7252					
$ModPCR_t$	0.2421	0.0580	0.1733	1			
	0.1711	0.1445	0.2050				
	0.2265	–0.1173	–0.0070				
$MFIS_t$	–0.4432	0.2081	–0.2449	–0.1865	1		
	0.2013	0.3307	0.2115	–0.1097			
	–0.5958	0.2380	–0.2868	–0.1781			
σ_t^{smirk}	0.0138	–0.2268	–0.1279	–0.0844	–0.3917	1	
	–0.0400	–0.3215	–0.3178	–0.0400	–0.4741		
	0.1781	–0.1398	0.1107	–0.0582	–0.5163		
VIX_t	–0.7057	–0.0745	–0.5137	–0.2783	0.4287	0.2313	1
	–0.4463	–0.4825	–0.6015	–0.3118	–0.1289	0.3960	
	–0.6645	0.1431	–0.2664	–0.2912	0.42213	0.0961	

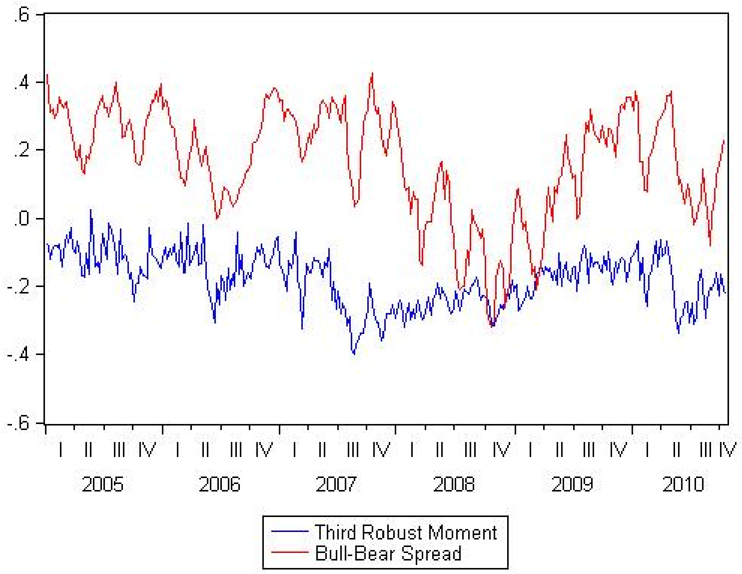

Figure 3.7: The weekly third robust moment η_t^3 for 30-calendar days from date t and the bull–bear spread, from January 2005 to October 2010.

Table 3.5: Regression results for the pre-crisis period pertaining to investor sentiment, p_t^{RND} regressed on BB_t^S. This is shown in equation (3.5).

Variable	Coefficient		Std. error	t-statistic	p-value
α	0.3070		0.0368	8.3434	0
p_{t-1}^{RND}	0.2899		0.0884	3.2813	0.0013
BB_t^S	0.0423		0.0209	2.0308	0.0444
R-squared	0.1596	Mean dependent var			0.4471
Adjusted R-squared	0.1462	S.D. dependent var			0.021
F-statistic	11.9622	Durbin–Watson stat			2.0767
Prob(F-statistic)	0				

weekly p_t^{RND} is regressed on the BB_t^S:[23]

$$p_t^{RND} \quad = \quad \alpha + \beta_1 p_{t-1}^{RND} + \beta_2 BB_t^S + \epsilon_t. \tag{3.5}$$

The weekly p_t^{RND} series is an AR(1) process, with MA(1) errors. The regression results for the entire period are statistically insignificant with respect to the independent variable BB_t^S. Examining data for the pre-crisis period between January 2005 and mid-2007 (the end of June), results obtained are in Table 3.5.

Adding this sentiment variable to the weekly AR(1) equation improves the adjusted R-squared value by approximately 2%. Hence there is a statistically significant, albeit negligible positive relationship between these two measures. This relationship alters in the post-crisis period, the relationship alters. The constant β_2 remains positive until the end of 2007; from July 2007 to the end of 2008, the coefficient is –0.01 with a p-value of 0.1. Thereafter, the relationship is statistically insignificant. This may then indicate that in times of uncertainty, surveys and trading data may be unrelated due to fundamental differences in their representation.

Given that p_t^{RND} is a forward-looking probability estimate based on investors beliefs of where the underlying is likely to end up at maturity conditional on current data, the possibility of a relationship between p_{t-i}^{RND}, where $i = 0,\ 1,\ 2,\ 3,\ 4$ and the time t bull–bear spread exists. Examining regressions up to a lag of four weeks for the pre-crisis period to determine whether

[23]All regressions have been adjusted to account for heteroscedasticity and serial correlation of standard errors according to Newey & West (1987).

Table 3.6: Regression results for the pre-crisis period, BB_t^S regressed on p_t^{RND}, as given in equation (3.6).

Variable	Coefficient		Std. error	t-statistic	p-value
BB_{t-1}^S	0.9214		0.0322	28.5893	0
p_t^{RND}	0.0414		0.0196	2.1092	0.0369
R-squared	0.8728	Mean dependent var			0.2430
Adjusted R-squared	0.8718	S.D. dependent var			0.0986
Durbin–Watson stat	1.6367				

this may be the case: [24]

$$BB_t^S \quad = \quad \beta_1 BB_{t-1}^S + \beta_2 p_{t-i}^{RND} + \epsilon_t \tag{3.6}$$

The results in Table 3.6 indicate that there is a statistically significant relationship at time t which is displayed below. The lagged regressions performed poorly and therefore, the results have been omitted. The same regression over the entire period results in $\beta_1 = 0.94$, $\beta_2 = 0.02$ (t-stats and p-values of 44.0 and 0, 1.6 and 0.11 respectively).

From July 2007, the relationship loses all statistical significance, however the sign of the coefficient as well as magnitude does not change. The lagged values of p_{t-i}^{RND} added in independently produce similar results (as the lagged values are themselves autocorrelated). Adding lags in succession serves to worsen the results. Thus, during the normal market regime, the contemporaneous probability measure p_t^{RND} displays a statistically significant relationship with BB_t^S. When the spread increases, so does the probability. This may imply that recent good performance implies a reversal may be expected in the near future.

Han (2007) performs an OLS regression where the bull–bear spread is regressed on the BKM $MFIS_t$ of the index return over the next month. The regressions employ monthly time series observations, as evaluated on the last trading day of each month. The sentiment proxies are measured on or prior to that date, using the latest available data. A lagged-dependent variable is included as a regressor to control for positive autocorrelation. The sample of data extends from

[24]The bull–bear spread is an AR(2) process, with constant approximately zero and lag coefficients 1.13 for AR(1) and –0.16 for AR(2) over the period 2005–2010. The adjusted R-squared value is 0.89. Altering the time period has a minimal effect upon the coefficients.

January 1988 to June 1997. Table 3.7 displays results for the entire period: [25]

$$MFIS_t \quad = \quad \alpha + \beta_1 MFIS_{t-1} + \beta_2 BB_t^S + \epsilon_t. \tag{3.7}$$

Table 3.7: Regression results for the entire period pertaining to BKM $MFIS_t$ as the dependent variable, and BB_t^S as the independent variable, as given in equation (3.7).

Variable	Coefficient		Std. error	t-statistic	Prob.
α	–0.4590		0.0613	–7.4831	0
$MFIS_{t-1}$	0.6969		0.0378	18.4333	0
BB_t^S	–0.3693		0.0877	–4.213	0
R-squared	0.5986	Mean dependent var			–1.7065
Adjusted R-squared	0.5959	S.D. dependent var			0.4092
F-statistic	222.9305	Durbin–Watson stat			2.2361
Prob(F-statistic)	0				

The above relationship, when examined over the subperiods, does not hold: the coefficient of BB_t^S is 0.65 for the period January 2005 to November 2006. [26] Thereafter, it becomes negative and is only statistically significant from January 2008 onwards. Regression results for the period January 2008 to October 2010 are in Table 3.8.

Table 3.8: Regression results for the period January 2008 to October 2010 pertaining to BKM $MFIS_t$ and BB_t^S, as given in equation (3.7).

Variable	Coefficient		Std. error	t-statistic	Prob.
α	–0.5182		0.0812	–6.3872	0
$MFIS_{t-1}$	0.6534		0.0536	12.1993	0
BB_t^S	–0.7074		0.1489	–4.7505	0
R-squared	0.7383	Mean dependent var			–1.7359
Adjusted R-squared	0.7329	S.D. dependent var			0.3978
F-statistic	136.8389	Durbin–Watson stat			2.2478
Prob(F-statistic)	0				

Han (2007) finds a positive coefficient for monthly BB_t^S. Han surmises that the risk-neutral skewness of the monthly index return is more negative when the market sentiment becomes more bearish. Hence to reconcile this, a monthly frequency regression is performed which results; over the period, $\beta_2 = 0.11$ (t-statistic 2.75, p-value 0.01). The above regressions indicate that the relationship between the BKM $MFIS_t$ and BB_t^S cannot be considered robust across subperiods

[25] The weekly $MFIS_t$ for the entire period is an AR(1) process; the errors are also an AR(1) process.

[26] The standard error is 0.22, t-statistic 2.99 and p-value 0.00.

or frequency. The η_t^3 measure is also addressed to assess performance. In replacing the BKM skew with η_t^3 in the weekly regressions, the p-value associated with β_2 was in excess of 0.1. Hence in this instance, the survey results failed to explain any of the residual variance in the third robust moment. Granger causality runs from η_t^3 to both the BKM $MFIS_t$ and the BB_t^S. Hence this indicates the implied skewness may in fact contain forward-looking information which is superior to that of the BKM skew measure.

Overall, weekly data regressions suggest that an increase in bullish sentiment is contemporaneously accompanied with an increase in the skew (less negative) and a slight increase in the probability measure, in the pre-crisis period. These relationships are insignificant thereafter. The relationship for the entire period when BB_t^S is regressed on $MFIS_t$ is contrary to that seen during the pre-crisis period: the coefficient of –0.37 for BB_t^S implies that as the survey sentiment results increase, the skew becomes more negative. This relationship holds for the crisis period as the bull–bear spread becomes negative. A negative skew implies a longer left tail with the median of the distribution to the right of the mean. The median divides the distribution into equal probability weight. The relationship with the VIX is robust across periods and is such that an increase in the VIX has the effect of decreasing the bull–bear spread (as was seen in the correlation table).

The bull–bear spread seems to react to recent returns and ultimately declines during bear markets. The definition of the spread omits the group of investors that believe a correction is due – this may imply the definition as a measure of institutional investor sentiment is deficient. The BKM $MFIS_t$ and p_t^{RND} are empirically derived and subject to the numerical method used. The relationships between the bull–bear spread and both the skew and the RND measure may fail to exist during crisis periods as the survey results capture momentum. This is in contrast to current option data which yields forward-looking probabilities of index levels at the relevant maturity, and therefore may not necessarily encapsulate the general malaise of the survey results. Frequency is also highly relevant as weekly and monthly results varied in the instance of the BKM skew.

The following section examines the daily data which are more relevant given the pertinence of measuring institutional investor sentiment at a higher frequency.

3.5.5 Daily Sentiment Results

The following section seeks to understand the relationships between variables over the identified market regimes.

The Probability Sentiment p_t^{RND}

This section seeks to establish whether the daily residual variance of p_t^{RND} can be explained by movements in other option-related variables over the identified periods. Having observed the discrepancies that exist in the weekly survey and option-implied sentiment measures, further analysis of the p_t^{RND} at a higher frequency may clarify dependencies. Hence, consistency is required. The PCR and modified version thereof have been omitted as they have performed poorly. Units are fractions of 100 (p_t^{RND}, VIX, σ_t^{smirk}) or as defined by the measurement.

OLS regressions are examined for the three periods identified with p_t^{RND} as the dependent variable, including a lag and ARMA(1,1) errors. All errors will also be accounted for by including ARMA terms when necessary. The OLS regressions over the subperiods are in Tables 3.9, 3.10 and 3.11. Results are for the following:

$$p_t^{RND} \quad = \quad \alpha + \beta_1 p_{t-1}^{RND} + \beta_2 \text{variable}_t + \epsilon_t. \tag{3.8}$$

The regressions indicate that both the VIX and the σ_t^{smirk} performed poorly in the second half of the sample period; the VIX appears to be the variable which has the least significance within the regressions. The remainder of the variables remain consistent in their relationship with p_t^{RND}. In particular, η_t^3 improves the adjusted R-squared value considerably, assuming the MA(1) error term is omitted. Table 3.12 provides the effect of a 0.1 increase in the variables to p_t^{RND}. Both the $MFIS_t$ and η_t^3 are primarily negative, and therefore the implication is that when the implied return distribution is less negatively skewed, the probability measure tends to increase. This was also confirmed for the weekly frequency. $\sigma_t^{smirk} > 0$ by definition as the OTM puts have higher implied volatilities than ATM call options. Thus an increase in the smirk implies that either the OTM put volatilities have increased or the ATM call volatilities have decreased, or both. A greater smirk is associated with a more bearish sentiment, so the negative coefficient implies that when the smirk increases and the distribution is more negatively skewed, the probability measure

Table 3.9: The Newey–West OLS regression results for the entire daily sample period with t-statistics and p-values. For the regression including η_t^3, the MA(1) error term has been removed and the adjusted R-squared of 0.64 refers to the regression prior to adding in the exogenous variable with a lag and AR(1) error term.

p_t^{RND}	variable					
2005–2010	α	0.0062	0.0075	0.0081	0.1348	0.0061
t-stat.		3.2871	3.9284	3.8160	16.3636	3.2330
p-value		0.0010	0.0001	0.0001	0	0.0012
	p_{t-1}^{RND}	0.9860	0.9846	0.9832	0.7170	0.9861
		231.8230	237.4303	218.3894	41.2868	232.1495
		0	0	0	0	0
	$MFIS_t$		0.0004			
			2.8790			
			0.0040			
	σ_t^{smirk}			–0.0072		
				–2.0120		
				0.0435		
	η_t^3				0.0527	
					13.1997	
					0	
	VIX					0.0001
						0.2414
						0.8092
Adj R-squared		0.6620	0.6626	0.6620	0.6677	0.6613
					0.6370	

decreases. Therefore, the more negative the skew (both $MFIS_t$ and η_t^3) and the greater the smirk σ_t^{smirk}, the less positive the probability measure. η_t^3, as defined by equation (3.1), provides a unique means to identify where the mass within the distribution is concentrated. Since it is usually negative, it is clear that $(U_{50} - U_{10}) > (U_{90} - U_{50})$. As before, U_x refers to the xth percentile of the return distribution. The measure p_t^{RND} is the cumulative sum of $f(S_T)$ – the probability density function derived from the PCA – given by $\sum_{k=1}^{i*} f_k(S_T)\Delta S_T = \mathbb{P}[S_T \leq s_t]$. Here, i^* represents that index such $\sum_{k=1}^{i*} \Delta S_T = s_t$ and let the probability measure be such that $U_* = \mathbb{P}[S_T \leq s_t]$. We have that $U_{10} < U_* < U_{50}$. If η_t^3 becomes more negative, the mass of the distribution moves towards the left and more weight is associated with negative outcomes. As this occurs, it seems that U_* tends to move to the left (the probability decreases). The strong and consistent negative correlation between σ_t^{smirk} and $MFIS_t$ further serves to emphasise the fact that the RND is more negatively skewed when the smirk is higher. The relationship with the VIX and the $MFIS_t$ is not clear from the correlations as the signs differ during the pre-crisis and crisis periods. This is explored further in the following section.

Table 3.10: The first half of the sample: January 2005 to June 2007. The MA(1) error term has been omitted for the regression with η_t^3, using equation (3.8).

p_t^{RND}	variable					
2005 to mid-2007	α	0.0076	0.0142	0.0144	0.1800	0.0193
t-stat.		2.1315	3.3450	3.1288	11.5484	3.4741
p-value		0.0333	0.0009	0.0018	0	0.0005
	p_{t-1}^{RND}	0.9830	0.9727	0.9729	0.6241	0.9640
		124.0200	114.3261	107.5479	19.0431	88.0886
		0	0	0	0	0
	$MFIS_t$		0.0011			
			3.0697			
			0.0022			
	σ_t^{smirk}			–0.0246		
				–2.4470		
				0.0146		
	η_t^3				0.0904	
					7.8012	
					0	
	VIX					–0.0254
						–3.4804
						0.0005
Adj R-squared		0.5538	0.5583	0.5571	0.5721	0.5596
					0.5251	

The VIX

In order to further understand the relationship between p_t^{RND}, $MFIS_t$, σ_t^{smirk}, η_t^3 and the VIX, these relationships are explored further below in order to establish their reliability as well as perceived response to market conditions. Figure 3.8 shows is the daily VIX from January 2005 to October 2010; the index attains its maximum value in November 2008.

Examining the relationship between the VIX and the returns using the daily data between 2005 and 2010, the following regression is evaluated with results [27] in Table(3.13):

$$VIX_t \quad = \quad \alpha + \beta_1 VIX_{t-1} + \beta_2 \ln\left(\frac{S_t}{S_{t-1}}\right) + \epsilon_t. \tag{3.10}$$

[27]Looking at the AR(1) for the VIX:

$$VIX_t \quad = \quad \alpha + \beta VIX_{t-1} + \epsilon_t, \tag{3.9}$$

The adjusted R-squared value increases by almost 10% from 0.87 (2005 to mid-2007), to 0.98 (mid-2007 to 2010), becoming non-stationary. Over the entire period, the value is 0.99 with $\beta = 0.99$.

Table 3.11: The second half of the sample: July 2007 to October 2010, as in equation (3.8).

p_t^{RND}	variable					
Mid-2007 - 2010	α	0.0069	0.0088	0.0082	0.1230	0.0070
t-stat. p-value		2.5973	3.0183	2.8423	6.2318	2.6136
		0.0095	0.0026	0.0046	0	0.0091
	p_{t-1}^{RND}	0.9843	0.9821	0.9827	0.7469	0.9837
		163.7099	159.5284	157.8080	18.6729	158.5262
		0	0	0	0	0
	$MFIS_t$		0.0005			
			2.0855			
			0.0372			
	σ_t^{smirk}			–0.0056		
				–1.3471		
				0.1782		
	η_t^3				0.0544	
					5.1844	
					0	
	VIX					0.0005
						0.6185
						0.5363
Adj R-squared		0.7295	0.7304	0.7297	0.7398	0.7294
					0.7120	

Table 3.12: The change in p_t^{RND} as a result of a contemporaneous increase of 0.1 for each of the variables taken independently of each other, for the entire sample period followed by the pre-crisis and post-crisis periods.

variable	Δp_t^{RND}
$MFIS_t$	0.0000428
	0.0001053
	0.0000513
σ_t^{smirk}	–0.000717
	–0.002463
	–0.000563
η_t^3	0.0052676
	0.0090427
	0.0054423
VIX	0.0000118
	–0.002541
	0.0000527

Over the entire time period, the adjusted R-squared valued improves by roughly 1% when the returns are included. Including additional lagged values serves to worsen the results. Including dummy variables for days when the index return is negative serves to reinforce the asymmetric relationship: An index decline is accompanied by an increase in the VIX which exceeds that

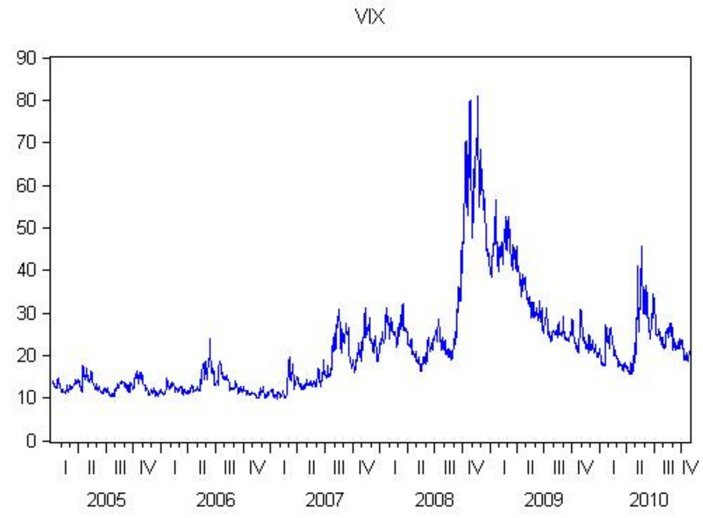

Figure 3.8: The daily VIX January 2005 to October 2010.

Table 3.13: Daily results of the VIX regressed on the index return over the entire period as provided in equation (3.10).

Variable	Coefficient		Std. error	t-statistic	p-value
α	0.0018		0.0005	3.6663	0.0003
VIX_{t-1}	0.9917		0.0028	356.5090	0
$\ln \frac{S_t}{S_{t-1}}$	–1.1304		0.0539	–20.9709	0
R-squared	0.9948	Mean dependent var			0.2177
Adjusted R-squared	0.9948	S.D. dependent var			0.1179
F-statistic	2042	Durbin–Watson stat			1.8991
Prob(F-statistic)	0				

which is accompanied by an equal-in-magnitude increase in the index. [28]

From Table 3.10 it can be seen that an increase of 1% in the VIX (when the value of the index goes up by one unit which is equivalent to 0.01) results in a decrease of 0.025 in p_t^{RND}. This occurs in the pre-crisis period during which the relationship is significant. The interpretation is such that the probability assigned to the index exceeding the current ATM futures level increases. Thereafter, the VIX trends upwards until it reaches the maximum, as shown in Figure 3.8.

[28] Over the pre-crisis period, including dummy variables defined by $D_1 = 1_{R_{t,t+1}>0}$ and $D_2 = 1_{R_{t,t+1}<0}$ separately (where $R_{t,t+1} = \ln \frac{S(t)}{S(t+1)}$) results in $\beta_{D_1} = 0.001$ (p-value$=0.03$), and $\beta_{D_2} = -0.001$ (p-value$=0.01$). Over the entire period, D_1 retains sign and magnitude yet the significance thereof is reduced whilst D_2 retains statistical significance and numerical properties.

The change in the level of the VIX is negatively related to the contemporaneous index returns (Whaley 2008), and therefore one may expect that an increase in the index, or equivalently a positive return, is accompanied by a decrease in the VIX. However, since the relationship is asymmetric, a decrease in the index will lead to an increase in the VIX by an amount larger than for the equivalent index increase. For consistency, one may expect to see that a decrease in the index results in a decrease in p_t^{RND}. This relationship holds for the pre-crisis period as the coefficient of the log-return is 0.30 (statistically significant, p-value of 0.004; t-statistic of 2.92). Relationships that hold during normal market regimes appear to lose significance in the post-crisis period – the coefficient of the VIX in Table 3.11 is close to zero. The relationship between p_t^{RND} and $\ln \frac{S(t)}{S(t+1)}$ over the period mid-2007 to 2010 becomes insignificant.

The Risk-Neutral Skew of BKM

The daily $MFIS_t$ is an AR(1) process, with errors that are also an AR(1) process over then entire period. The model in Table 3.14 best fits the daily data, with the following regression performed:

$$MFIS_t \quad = \quad \alpha + \beta MFIS_{t-1} + \epsilon_t, \tag{3.11}$$

Table 3.14: Daily data for the BKM $MFIS_t$ over the entire sample period; the equation estimated to fit the data is given in (3.11).

Variable	Coefficient		Std. error	t-statistic	Prob.
α	–0.0878		0.0167	–5.2594	0
$MFIS_{t-1}$	0.9492		0.0100	96.8116	0
AR(1)	–0.2899		0.1085	–2.6727	0.0076
R-squared	0.8414	Mean dependent var			–1.7240
Adjusted R-squared	0.8412	S.D. dependent var			0.4250
F-statistic	5624.818	Durbin–Watson stat			2.0329
Prob(F-statistic)	0				
Inverted AR roots	–0.29				

Regressing the BKM $MFIS_t$ on the other option-related measures (including an AR(1) error term), results are in Tables 3.5.5, 3.5.5 and 3.5.5. The regressions are performed over the entire sample period, followed by the periods January 2005 to July 2008 and August 2008 to October

2010. The reason for extending the pre-crisis period can be seen from examining Figure 3.8. The time series trends upwards from mid-August 2008 until it reaches a maximum of 81% in November 2008. This is the highest level recorded during this period. The adjusted R-squared value over the extended pre-crisis period is much higher. The global financial crisis of September–October 2008 resulted in huge losses in stock markets worldwide. Figure 3.9 displays the S&P 500 index daily close; a low occurred in early March 2009.

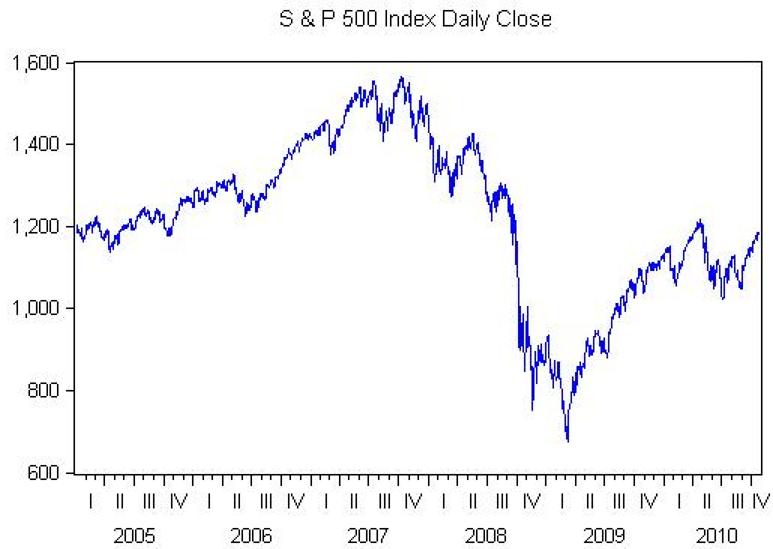

Figure 3.9: The daily S&P 500 index close from January 2005 to October 2010. The

$$MFIS_t \quad = \quad \alpha + \beta_1 MFIS_{t-1} + \beta_2 \text{variable}_t + \epsilon_t. \tag{3.12}$$

The relationship between $MFIS_t$ and the VIX is much like that between p_t^{RND} and the VIX, however the order of significance has been reversed: it is negative and insignificant in the first period and reverts to being positive and significant in the second period. During the pre-crisis period, both the S&P 500 index and the VIX were trending upwards. The relationship with the $MFIS_t$ during this period is insignificant. In the second period, the VIX reaches a high of over 80% during November 2008. In this period the S&P 500 index experiences extreme declines. Therefore, the risk-neutral skewness, being positively related to VIX movements, seems to increase (less negative). Han (2007) finds the coefficient of the VIX to be positive; the data

Table 3.15: The entire sample from January 2005 to October 2010. For the regressions involving p_t^{RND}, the constant term as its t-statistic and p-value is not significant.

$MFIS_t$	Variable					
2005–2010	α	–0.0878	0	–0.0562	–0.1129	–0.1368
t-stat.		–5.2594	–	–3.6080	–5.4276	–5.7079
p-value		0	–	0.0003	0	0
	$MFIS_{t-1}$	0.9492	0.9533	0.9378	0.9447	0.9347
		96.8116	106.5709	83.7091	92.2890	80.5733
		0	0	0	0	0
	p_t^{RND}		–0.1816			
			–5.2917			
			0			
	σ_t^{smirk}			–0.5057		
				–3.5082		
				0.0005		
	η_t^3				–0.0971	
					–2.6620	
					0.0078	
	VIX					0.1117
						4.4786
						0
Adj R-squared		0.8412	0.8412	0.8422	0.8416	0.8424

consisted of 114 month-end observations of each variable from January 1988 to June 1997. Here, the positive coefficient is only apparent in the second period. The only relationships that are consistent in sign and significant across regimes are those with p_t^{RND} and σ_t^{smirk}.

Table 3.18 provides the effect of a 0.1 increase of each of the variables on $MFIS_t$, whilst others remain constant. What can be seen is that an increase in the probability measure implies a more negative BKM skewness, and an increase in the smirk is accompanied by a decrease in $MFIS_t$. The relationship with η_t^3 is not consistent across the regimes. The relationship between the $MFIS_t$ and η_t^3 is unclear: The former is derived from the method in Rehman & Vilkov (2010) and the latter is a purely numerical construct of the RND derived using PCA.

In an attempt to reconcile this observation with the results obtained for p_t^{RND}, Table 3.12 indicates that when both the $MFIS_t$ and η_t^3 are less negative, there will be an increase in the probability measure. An increase in the smirk, σ_t^{smirk}, serves to decrease the probability measure however this relationship is statistically insignificant in both periods. A decrease in σ_t^{smirk} results in a more negative $MFIS_t$. Thus, as the OTM put implied volatility increases, there is more probability mass in the left side of the returns distribution.

Table 3.16: The regressions of $MFIS_t$ on variables, as in equation (3.12) for the pre-crisis sample. Once again the constant term is omitted for the exogenous variable p_t^{RND}.

$MFIS_t$	Variable					
2005 to mid-2007	α	–0.1832	0	–0.0905	–0.1736	–0.1314
		–4.1867	–	–2.4498	–4.0819	–2.9082
		0	–	0.0145	0	0.0037
	$MFIS_{t-1}$	0.9034	0.9187	0.8675	0.8994	0.8992
		38.7159	45.9229	31.7064	37.6648	37.3733
		0	0	0	0	0
	p_t^{RND}		–0.3435			
			–4.1085			
			0			
	σ_t^{smirk}			–1.6929		
				–4.1841		
				0		
	η_t^3				0.1310	
					1.3937	
					0.1638	
	VIX					–0.4632
						–1.6173
						0.1062
Adj R-squared		0.6973	0.6953	0.7038	0.6976	0.6979

Table 3.17: The regressions of $MFIS_t$ on variables, as in equation (3.12) for the post-crisis sample.

$MFIS_t$	Variable					
Mid-2007 to 2010	α	–0.0560	0	–0.0328	–0.0809	–0.0988
		–4.4634	–	–2.4376	–4.9907	–5.3151
		0	–	0.0149	0	0
	$MFIS_{t-1}$	0.9651	0.9686	0.9457	0.9613	0.9539
		120.9153	133.8201	77.9738	121.8398	106.0824
		0	0	0	0	0
	p_t^{RND}		–0.1133			
			–4.4084			
			0			
	σ_t^{smirk}			–0.5077		
				–2.8257		
				0.0048		
	η_t^3				–0.0893	
					–2.0535	
					0.0402	
	VIX					0.0882
						3.5796
						0.0004
Adj R-squared		0.9179	0.9177	0.9187	0.9181	0.9184

Table 3.18: The change in $MFIS_t$ as a result of a contemporaneous increase of 0.1 for each of the variables taken independently of each other, for the entire sample period followed by the pre-crisis and post-crisis periods.

Variable	$\Delta MFIS_t$
p_t^{RND}	–0.01816
	–0.03435
	–0.01133
σ_t^{smirk}	–0.05057
	–0.16929
	–0.05077
η_t^3	–0.00971
	0.013099
	–0.00893
VIX	0.011173
	–0.04632
	0.008818

Examining the relationship with contemporaneous returns, the results in Table 3.19 are obtained when including a lag and accounting for an AR(1) error term:

$$MFIS_t = \alpha + \beta_1 MFIS_{t-1} + \beta_2 \ln\left(\frac{S_t}{S_{t-1}}\right) + \epsilon_t. \tag{3.13}$$

Table 3.19: The BKM skew regressed on daily log-returns over the period specified, as shown in equation (3.13).

	Variable	Coefficient	Std. error	t-statistic	Prob.	Adj R-squared
2005–2010	α	–0.0549	0.0105	–5.2492	0	0.9253
	$MFIS_{t-1}$	0.9681	0.0060	162.7513	0	
	$\ln\frac{S_t}{S_{t-1}}$	–3.8078	0.3912	–9.7327	0	
January 2005 to	α	–0.0751	0.0147	–5.1018	0	0.895365
July 2008	$MFIS_{t-1}$	0.9578	0.0082	116.3959	0	
	$\ln\frac{S_t}{S_{t-1}}$	–5.8624	0.5267	–11.1303	0	
August 2008 to	α	–0.0457	0.0160	–2.8450	0.0046	0.9575
October 2010	$MFIS_{t-1}$	0.9720	0.0095	102.7698	0	
	$\ln\frac{S_t}{S_{t-1}}$	–3.3745	0.4719	–7.1515	0	

Contemporaneous negative returns give rise to a less negative skew. Han (2007) finds that momentum, when included as a control variable, is positively related to the risk-neutral skewness: past good returns serve to increase the skew. Momentum is closely tied to the BB_t^S, and therefore past good performance leads to a higher percentage of bullish opinions (positive sentiment) and a less negative risk-neutral skewness. However, Chen, Hong & Stein (2002) finds that past high returns are followed by a more negative conditional expected skewness. Given that the $MFIS_t$ has an inconsistent relationship with BB_t^S across regimes, the same is evident when considering momentum and $MFIS_t$. Examining the regression with the daily log-returns, it is evident that the $MFIS_t$ here seems to be indicative of a perceived reversal in the market. This negative relationship holds when looking at weekly regressions for log returns of up to eight weeks. Thereafter, the results are insignificant.

The Robust Moment η_t^3

To determine the relationship between the third robust moment η_t^3 and the VIX, an OLS regression uses the daily data, including an MA(1) error term. [29] The following regression is estimated:

$$\eta_t^3 \quad = \quad \alpha + \beta_1 \eta_{t-1}^3 + \beta_2 VIX_t + \epsilon_t. \tag{3.14}$$

Table 3.20: The third robust moment regressed on the VIX over the period specified, as shown in equation (3.14).

	Variable	Coefficient	Std. error	t-statistic	Prob.	Adjusted R-squared
2005–2010	α	–0.0038	0.0009	–4.2491	0	0.8530
	η_{t-1}^3	0.9616	0.0061	158.6546	0	
	VIX	–0.01421	0.0034	–4.2330	0	
January 2005 to July 2008	α	0.0046	0.0017	2.6905	0.0072	0.8601
	η_{t-1}^3	0.8962	0.0131	68.5410	0	
	VIX	–0.1430	0.0208	–6.8844	0	
August 2008 to October 2010	α	–0.0061	0.0019	–3.1292	0.0018	0.8473
	η_{t-1}^3	0.9278	0.0147	63.2755	0	
	VIX	–0.0238	0.0060	–4.0275	0.0001	

An increase in the VIX is associated with a more negative skew, as measured by η_t^3. Bondarenko (2000) uses the robust moments approach to generate a time series for skewness, η_t^3 for the maturity $m = 2$. Performing an OLS regression of the robust moments on current and lagged log-returns of daily data over the period of January 1991 to December 1995, Bondarenko finds that $\beta_2 > 0$. Negative returns are associated with an implied RND which is more negatively

[29] The time series follows an AR(1) process with errors that are MA(1).

skewed, indicating that investors become pessimistic when the index performs poorly. Dennis & Mayhew (2002) also find that skewness of individual stock options decrease when market volatility increases. The results for the $MFIS_t$ time series did not display the same robustness across periods. Estimating the same regression, including an AR(1) term for the dependent variable, and an ARMA(1,1) error term over the adjusted periods:

$$\eta_t^3 \quad = \quad \alpha + \beta_1 \eta_{t-1}^3 + \beta_2 \ln\left(\frac{S_t}{S_{t-1}}\right) + \epsilon_t. \tag{3.15}$$

Table 3.21: The third robust moment regressed on the daily log-returns over the period specified, as in equation (3.15).

	Variable	Coefficient	Std. error	t-statistic	Prob.	Adjusted R-squared
2005–2010	α	–0.0045	0.0012	–4.1869	0	0.7820
	η_{t-1}^3	0.9792	0.0050	198.0527	0	
	$\ln\frac{S_t}{S_{t-1}}$	0.2045	0.0734	2.7844	0.0054	
January 2005 to July 2008	α	–0.0032	0.0011	–3.0172	0.0026	0.7940
	η_{t-1}^3	0.9850	0.0051	191.9162	0	
	$\ln\frac{S_t}{S_{t-1}}$	0.3819	0.1478	2.5842	0.0099	
August 2008 to October 2010	α	–0.0071	0.0025	–2.8929	0.0039	0.7590
	η_{t-1}^3	0.9666	0.0110	87.5714	0	
	$\ln\frac{S_t}{S_{t-1}}$	0.1402	0.0815	1.7198	0.0858	

Comparing this to the $MFIS_t$, it is clear that these two measures of skewness display contradictory results, the standard error in the latter case being fairly high across time periods. Han (2007) found that risk-neutral skewness was more negative as investors became more bearish. The weekly relationship between the BKM risk-neutral skewness and the bull–bear spread is not consistent across regimes: an increase in bullish sentiment seems to be accompanied by a less negative skew in the pre-crisis period. Thereafter, the statistical significance breaks down. The $MFIS_t$ does not show a consistent relationship with the VIX either. With regard to contemporaneous returns, the negative coefficient implies that current positive returns serve to decrease the risk-neutral skew further. This is in contrast to the results reported in Bondarenko (2000) which indicate that the coefficient of contemporaneous returns is positive, as is displayed in the above OLS regression with η_t^3. The results of $MFIS_t$ with the VIX are inconsistent and agree with those in Han (2007) during the crisis period. In this instance, an increase in the VIX increases the $MFIS_t$. In comparison, with η_t^3, there is a consistent negative relationship to the VIX and a positive consistent relationship to contemporaneous returns. It is also the case that as η_t^3 decreases, so too does the probability measure. This is rather intriguing; however, accounting for the fact that the grid is specified using $5 equidistant spacing, it seems to be the case that the futures level lies slightly to the left of the median. As the grid size alternates, the probability alters, however not in a systematic way. Therefore, results are always subject to numerical limitations. In the Black–Scholes case, all grids produce the same results.

In order to disentangle the above results, each variable is listed separately, with corresponding relationships to other variables.

3.6 Interpretation of Results

Given the numerous regressions performed above over different market regimes and frequencies, it is crucial to examine each indicator in isolation to determine what relationships can be used with confidence as a means to establish the supreme indirect measure of institutional investor sentiment. Sentiment is more appropriately defined with respect to aggregate beliefs based on the demand for insurance. It may not necessarily refer to other definitions such as the 'aggregated errors in beliefs', or 'beliefs formed from everything but fundamental value'.

3.6.1 The Bull–Bear Spread

This measure, which is based on the difference between bullish and bearish newsletter writers, is a survey-based result and serves to provide a weekly institutional sentiment measure. This appears to be the most suited measure to use when establishing the merits of other possible measures. The drawbacks of using such a measure is the relationship to momentum: the past six-month index returns Granger-cause the BB_t^S time series. Thus, one should caution the use and applicability as it pertains to historical market performance, and not necessarily current or future sentiment. Brown & Cliff (2004) find that the recent return is the most important determinant of market sentiment.

From section 3.5.4, there was very little evidence to suggest that any of the measures derived from trading activity are consistent with the BB_t^S or display any significance across sub-periods considered. Segmenting the entire time period enables the relationships to be explained precisely and within context of market conditions. The bull–bear spread is positively correlated to the VIX and to η_t^3. The remainder of the variables alternate in sign across periods. It is also positively correlated to the modified put–call ratio.

Examined independently, a bullish sentiment increase is accompanied by an increase in the VIX. Seeing that the bull–bear spread is a weekly measure based on momentum, movements in the VIX (both values are those that correspond to the date t, the VIX is not an average of the previous week) could indicate the survey results are a contrarian indicator for current market conditions. The daily VIX is highly autocorrelated and increases when the market declines. Regressions whereby the independent variable is the VIX and the dependent variable the BB_t^S do not provide any convincing or significant relationships, thus the correlations should be treated with caution. The correlation of BB_t^S to η_t^3 seems to agree with the result of Han (2007): a less negative skew is indicative of bullish market sentiment. This relationship, over the sub-periods, is statistically insignificant when η_t^3 is regressed on BB_t^S. The modified PCR is a weighted average of the volume of all OTM puts to OTM calls (SPX options). The way such trades may affect the implied volatility, and consequently the RND, is through the demand and supply thereof. As discussed in Bollen & Whaley (2004), the upward sloping supply curve results in higher implied volatility for certain options. However, this parameter displays no clear relationship to the remaining variables.

Considering the regressions results, none of the variables considered displayed a consistent and significant relationship to the bull–bear spread. Regarding the risk-neutral skew of BKM, the results are in contrast to the monthly regressions performed by Han (2007). This may have arisen as the method employed here interpolated implied volatility, prior to calculating the integrals, discussed in Rehman & Vilkov (2010). Regardless of what may have been the cause of this, the results indicate that neither the BKM $MFIS_t$ or η_t^3 contain information relating to survey data. Nor does the probability measure RND_t^b. Thus the question arises: what can be understood about market sentiment from the information contained in the RND and from that of the higher moments?

To further answer this, those relationships will be clarified below.

3.6.2 The Probability Measure p_t^{RND}

Option contracts provide the means with which to hedge the market's decline and to benefit from any speculative gains. The probability attached to attaining the current ATM futures level is that probability which may provide insight into whether the aggregate market perceives an increase or a decrease. Hence, the cumulative probability derived from the RND has been selected as the variable of interest, with those of the higher moments: the VIX and the skew (both risk-neutral $MFIS_t$ and that of the robust moments approach η_t^3) and the smirk, σ_t^{smirk}.

Examining the correlations is a first step to gauge consistent relationships between the p_t^{RND} and the remaining variables. The PCR and modified PCR are ruled out at this stage as further results (which have been omitted) serve to confirm their insignificance. Regressions in section 3.5.5 for both the $MFIS_t$ and η_t^3 (more so in the second instance) display a consistent positive relationship with p_t^{RND}. That is, an increase in the skew (less negative) results in an increase in the probability measure. A consistent negative relationship, although insignificant in the crisis period, exists between the smirk and the probability; as the smirk increases, the probability measure decreases. In total, the more negatively skewed the distribution, the greater the smirk, and the less the probability measure. This then implies that p_t^{RND} is in fact a bearish sentiment measure, assuming the remaining variables are indeed closely related to current market sentiment. If it is the case that an increase in the smirk and a decrease in the skew implies a decrease in market sentiment, then one may assume that the overall relationship that exists between these variables as a combined measure, can be used as reference relative to historical levels, much like the VIX serves as a 'fear gauge'.

3.6.3 The BKM $MFIS_t$

The most notable and surprising result when establishing the merits of the risk-neutral measure of Bakshi et al. (2003) is that the relationship to the weekly bull–bear spread does not hold here using weekly data; monthly data were more in line with Han (2007). Whether the survey result is indeed an artefact of historical performance is not being questioned, however the applicability thereof as a sentiment measure that is current should be regarded with caution. This does not imply that the $MFIS_t$ should be considered a replacement thereto, however market trades cannot be superseded by stale data, which is primarily what a survey result may provide. The evidence here conflicts with the monthly results of Han (2007) with regard to momentum as well as the VIX.

Considering the OLS regressions in section 3.5.5, the relationship with p_t^{RND} is such that as the probability measure increases, the distribution is more negatively skewed. Examining Granger causality, it is the case that the BKM $MFIS_t$ Granger-causes the probability measure. The relationship between $MFIS_t$ and η_t^3 is inconsistent. Seeing that both are skewness measures of the same data, the relationship that exists is incomprehensible within the context of the regression data. The relationship with the VIX is inconsistent across sub-periods, and significant in the crisis period indicating that an increase in the VIX is accompanied by a less negative $MFIS_t$. This seems counterintuitive: as the market experiences severe declines (increases in the VIX), the perception of pessimistic outcomes is exacerbated. Han (2007) too found a positive coefficient when the skew was regressed on the VIX. The relationship to the smirk is robust across periods: an increase in the smirk serves to decrease the skew further which results from more probability mass in the left-hand side of the distribution.

Considering that momentum is positively related to the skew and the bull–bear spread, it is perplexing to see that $MFIS_t$ does not conform to these relationships. In particular, when examining the relationship with the daily log-returns, it was surprisingly the case that positive contemporaneous returns were accompanied by a decrease in the risk-neutral skew. This then implies that current positive returns creates future bearish sentiment, as measured by the skew. This is at odds with the optimism that usually is accompanied by positive returns; in fact, the reverse holds true for η_t^3 as there is a positive relationship with contemporaneous daily returns, as well as momentum.

Examining the above, one can only conclude that the varied and somewhat unexpected relationships that exist yields the $MFIS_t$, as calculated according to the method described in section 3.2.2, is indeterminate. Therefore, this raises the question of the validity of previous results.

3.6.4 The Robust Third Moment η_t^3

The robust moments approach is a purely numerical construct derived as a means to adapt the moments of the Black–Scholes lognormal returns distribution as determined numerically by PCA; they are arbitrary in nature. Examining the third of such moments serves to indicate the statistical significance and therefore, possible relevance thereof. Consistent relationships that exist between η^3, p_t^{RND}, the VIX and the daily log-returns give credence to such a construct, irrespective of the insignificance of the relationships with the weekly BB_t^S or $MFIS_t$.

In summary, as η_t^3 becomes more negative, p_t^{RND} decreases. Granger causality runs in both directions as the variables are derived from the same construct. Increases in the VIX, which are accompanied by negative returns, serve to decrease η_t^3 further. η_t^3 is statistically significant and positively related to both contemporaneous daily log-returns, recent market movements (log-returns of up to two months) and momentum, as measured by the past six-month log-return. This is in line with the research of Amin, Coval & Seyhun (2004), and with the results found in Han (2007). η_t^3 also decreases as the smirk increases.

The results here firmly qualify this robust moment as a possible candidate to measure daily sentiment. Given the statistical significance of the relationship with other variables, the RND therefore gives rise to a higher moment which is consistent in terms of relationships with relevant variables.

3.6.5 The Smirk σ_t^{smirk}

The smirk is a measure of the slope of the implied volatility function and is calculated as the difference between the implied volatility of the OTM put options and the ATM call options. The purpose of inclusion here was as a control for the $MFIS_t$: the greater the smirk, the more negative the skew of the risk-neutral distribution. This holds true for both $MFIS_t$ and η_t^3. This agrees with the result in Han (2007) in which index risk-neutral skewness becomes more negative when there is a higher demand for the OTM index put options relative to the near and ATM index options. This is consistent with the relation between the relative demand of index options and the slope of the index option smile.

Regressions involving p_t^{RND} indicated that an increase in the smirk served to decrease the probability measure; the result was statistically insignificant in the second period. The VIX and the smirk exhibit positive correlation across periods indicating that increases in fear (VIX) lead to higher OTM put implied volatility or a lower ATM call implied volatility. No statistically significant relationship was seen to exist in response to movements in daily returns or momentum.

3.6.6 The VIX

Han (2007) selects control variables because they are related to the index option volatility smile skewness, since a negative index risk-neutral skewness is closely related to the index option volatility smile (Bakshi et al. 2003). The VIX is used as a proxy for the instantaneous volatility of index return and represents the average implied volatility of the ATM index options 30 days before expiration. Han finds that index risk-neutral skewness is less negative when market volatility is higher. The relationship between $MFIS_t$ and the VIX conforms to this during the crisis period. Contrary to this, the moment η_t^3 displays a negative and significant relationship with the VIX.

To account for such a discrepancy, one may attempt to explain both sets of results. The VIX increases as the market index declines. Such uncertainty leads market participants to seek out those investments which pay out in bad states of the world, driving up the prices of the OTM put options. Doing so further decreases the risk-neutral skew and increases the smirk. This is consistent with the daily log-returns, the VIX, η_t^3 and the smirk, σ_t^{smirk}. The relationship with p_t^{RND} is not as clear, however η_t^3 seems to be a preferable variable in this context. As for $MFIS_t$, it does not display a consistent relationship with the VIX nor seems to coincide with η_t^3 on various occasions. The results in Han (2007) seem to raise a question, specifically if recent positive returns (a lower level in the VIX) results in less negative skewness. Based on this, one should expect that the coefficient of the VIX, as an independent variable in an OLS regression, should be negative as is the case with η_t^3.

3.7 Conclusion and Practical Applications

This chapter has contributed to a broad spectrum of sentiment research by assuming that institutional investor sentiment is extracted from their trade decisions using equity index options. Further, using a fully non-parametric approach to find the RND, the cumulative probability as well as third robust moment have been examined in relation to both survey- and market-based measures. This has been performed using both weekly and daily frequencies (where applicable) which may render these measures far more suitable as a current measure of such sentiment. Additionally, these measures have been examined over different market regimes to find that η_t^3 is the most consistent measure. Multiple regressions have been performed to find η_t^3 to be the superior option-implied sentiment measure which is conditional on current pricing and reflects the outlook for the aggregate market over the next 30-day period, as measured on date t.

Index option markets are ostensibly a means to insure against equity declines for large institutional investors. Given the depth of these markets, the information content therein is indispensable. The RND that can be inferred for a given maturity reflects the beliefs of those investors. This research has attempted to convey the superior information pertaining to investor sentiment which is readily available on a daily basis. Extracting the RND using PCA yields both moments as well as the cumulative probability p_t^{RND} of aggregate investors. This shifts daily as do beliefs. Hence, p_t^{RND} renders itself suitable as a current forward-looking indirect sentiment measure.

In an effort to establish coherence between the selected variables, evidence suggests that although derived from a similar source data, some relationships give rise to contrasting results, contingent on the market regime and frequency of data. The survey-based measure BB_t^S is highly influenced by past performance as momentum Granger-causes the bull–bear spread. The volatility regime is also responsible for the conviction of the measure. Weekly BB_t^S regression results are unconvincing; proceeding to daily data, results between the probability measure p_t^{RND}, η_t^3, the VIX and σ_t^{smirk}, are consistent across market regimes.

In response to positive daily log-returns as well as positive momentum, the VIX declines and the skew η_t^3 becomes less negative. As this occurs, the probability measure increases. The σ_t^{smirk} decreases as η_t^3 increases. Thus, the implied volatilities as well as option prices which yield the RND, and in particular the probability p_t^{RND} and robust moment η_t^3, seem to be consistent with the VIX as well as the smirk when establishing perceptions about future stock market movements. These variables may serve as an indication of whether supply or demand factors are responsible for movements in the skew, and therefore the probability attached to attaining (or exceeding) the ATM futures level. Positive daily returns serve to increase both the skew η_t^3 and p_t^{RND}. Both the VIX and the smirk decrease; the latter failed to indicate a direct relationship to either returns or momentum, but rather to η_t^3. Short-term movements in the skew may be a result of spread betting and therefore this in conjunction with other RND implied measures may serve to be more useful as a sentiment indicator.

The RND is a numerical construct and, naturally, altering the input grid parameter is likely to effect the quantitative element of the relationships. However, the qualitative results remain intact over the period January 2005 to October 2010. The option-implied measures of the RND present a dynamic relationship which is consistent across time and can be used as a means to understand how market participants react to past and current market movement. The extent of such measurements relative to historical levels can be used as a means to establish the extent of bullish or bearish sentiment on a daily basis.

Sentiment is often used as relative measure to gauge perceptions regarding future market movements. The value is only ever meaningful in relation to the history. Practical applications for such measures are often limited to extracting a perception of the aggregate conditional outlook of such investors. In order to use the information content of any sentiment-related measure, one requires a strategy based on possible differences between the option-implied and actual sentiment which can be exploited for financial gain. The latter measure is often a subjective or forecasted value of the movement in the underlying. In particular, the moments of the RND have been previously sighted in a similar vane with reference to the impact of macro data releases on such measures. Ederington & Lee (1996) find that the uncertainty, as measured by the standard deviation of ATM options within the T-Bond, Eurodollar, and Deutschemark options markets, decreases after scheduled information releases. They find "...that market participants apparently do take into account the schedule of upcoming announcements in forming their expectations of likely future volatility." Given that implied standard deviations consistently fall following earnings announcements, they explore the possibility of a profitable trading strategy based on this. With respect to unscheduled announcements, implied standard deviations rise. Fornani & Mele (2001) examine prices of options and futures on Italian 10-year bonds with shortest maturity traded on LIFFE between 199 and 1997. The impact of news on the terminal points of the volatility smile are selected from the deepest ITM and OTM options, as opposed the the ATM options. News belongs to two categories: (i) scheduled news: CPI, PPI, at-issue yield of the T-bills ,repo rate of the Bank of Italy; (ii) unscheduled news: headline news from the Italian leading newspaper; news pertaining to the volatility of the exchange rate. The study was conducted in accordance with Ederington & Lee (1996) – they examine the effect of news on the implied standard deviation of options written on futures contracts with the shortest available maturity. Daily rates of change of the implied volatility (IV) of each moneyness level are regressed on the dummy variables which record the arrival of scheduled and unscheduled news; in general, the results are as expected. The (un)scheduled news coefficient takes a (positive) negative sign. In particular, the arrival of unscheduled bad news tends to increase the IV over the life of the option; good news does not alter the IV. For the case of scheduled news, only the release of the CPI was significant for ITM and OTM options, and reduced the expected variance on days of scheduled announcements. The slope and skewness of the volatility smile is affected by this news release: there's a reduction in the difference between OTM and ATM, as well as between the ITM and ATM options. In conclusion, the three extreme points of the volatility smile - ITM, ATM and OTM volatility - are affected by the arrival of news.

Of relevance here is the research of Bebera & Brandt (2006). The authors examine the state price density (SPD) of US Treasury bond markets shortly before and after macro news announcements. Regardless of content, the announcements reduce uncertainty in the second implied moment shortly after news release. The changes in the higher moments depend on the news content. Their results are consistent with time-varying risk aversion (habit formation) - they disentangle changes in beliefs from changes in preferences. Asset prices are a reflection of cash flows and discount rates. Riskfree government bonds have fixed cash flows and therefore, only the discount rates are relevant. The state price density is distinct from the objective probability density function (PDF) since it combines beliefs of market participants about the likelihood of certain states and their preferences towards these states. A high value might indicate that market participants believe the state to be relatively likely and/or dislike the state. Changes in the SPD due to macroeconomic announcements can be related to changes in either beliefs or preference. Thus, they examine how the SPD of bond prices changes in response to information releases and then disentangle the two components to infer the changes specific to beliefs and preferences respectively. Data: US Treasury bond futures prices from transactions from CBOT over a 5-year period (1995-1999). The SPDs are from the Edgeworth expansions around log-normal densities short before and after scheduled announcements are considered. Results indicate that news content is immaterial to the implied second moment of the SPD; the higher moments are not innocuous to such content. The direction and magnitude of the changes in higher order moments is contingent upon such content. They find"The SPD becomes less (more) negatively skewed and less (more) fat-tailed in response to bad (good) news for the bond market. Furthermore, the results are asymmetric, in that bad news has a greater impact on the higher-order moments of the SPD than does good news". They show that the changes in the higher-order moments are consistent with time-varying risk aversion. Bad news for the bond market leads market participants to become less risk averse and for the SPD to be more similar to the PDF. Bad news for the bond market implies good news for economic prospects. News announcements consists of the set of the following ten announcements, and is fairly complete: inflation, measured by the consumer price index (CPI) and producer price index (PPI); the situation in the labour market measured by the civilian unemployment rate (CUR) and non-farm payrolls (NFP); the dynamic of consumption by the retail sales (RS); the state of the economy by the industrial production (IP); the perceived state of the economy by consumer confidence (CC) and the national association of purchasing managers index (NAPM); the conditions of the money market by the Federal Open Market Committee federal funds target rate (FOMC) and the situation in the real estate market by housing starts (HS). Thus, the higher moments of the RND which have been used to infer sentiment of those investors that participate in the particular markets can be used to find strategies which exploit superior knowledge or forecasts of such macro data releases.

Chapter 4

Sentiment Propagation and Portfolio Insurance

4.1 Introduction

Sentiment within an economy need not be subject to influences which pertain exclusively to that domestic environment; the integration of financial markets and cross-border activity has become a conduit for current and forward-looking opinions, often resulting in capital flows based on these preferences. This is analogous to, and very much linked with, financial crises which tend to spread across borders due to the globalisation of economies. Global sentiment propagation has received little attention as most sentiment studies focus on specific financial markets; the measures are often representative of certain groups of investors. The focus of this research is to explore how sentiment (pertaining to financial markets) propagates. As mentioned in Chan, Faff & Hwang (2009), understanding sentiment contagion is important from an investment perspective as investors are concerned about adverse stock price movements, excess volatility, and increased correlation. The latter is particularly relevant as this reduces the benefits of diversification. Sentiment propagation is likely to be closely related to financial contagion.

Given that measuring sentiment within a specific financial market is subject to much debate, further investigation into the channels through which it filters across markets is therefore non-trivial. Survey-based measures and direct stock market activity attempt to merge often divergent opinions into an all-encompassing quantum. Thus, sentiment measures of a reference country may either be captured by responses of the demographic that partake in consumer/investor confidence surveys or are derived from domestic trading, respectively.

Consumer confidence indices exist for a number of developed and emerging markets. The results thereof are indicative of the general macroeconomic outlook and, given the monthly frequency, cannot readily be used as an accurate indication of investor sentiment pertaining to current and expected near-term market movements. The causal relationship between the stock market and consumer confidence has been established: momentum tends to positively affect confidence. Sentiment is ultimately an amalgamation of opinions which are then transformed into actions. Low-frequency macro news releases – output, trade and inflation data – establish the general perception of the current and expected macroeconomic environment. Stock markets tend to react to macroeconomic news of both the domestic and US economy, the dominant economy. This serves to enhance or refute investors' bullishness or bearishness. Within the context of financial markets, sentiment refers to the aggregation of attitudes of a select group of investors, retail or institutional. This will be discussed further in section 4.2.1.

Henceforth, sentiment will refer exclusively to the participants within financial markets as the trading activity therefrom provokes almost immediate effects due to the frequency of the transactions. High-frequency investor fund flows (trading activity) are thereby the direct means to observe investor sentiment with respect to asset class or region, with capital flows being the ultimate drivers of asset prices. This is crucial in order to understand financial crises and contagion. There are multitudes of measures which are constructed in order to capture the current sentiment of investors.

Fund flow data has been increasingly referenced as a viable means to gauge sentiment of a reference investor group, retail or institutional. Fund flows have been empirically shown to propel performance; it is also the case that superior performance of assets tends to draw funds. Due to this interplay, fund flows may exhibit inertia and therefore contain momentum information. There are however differences contingent upon which group of investors are under scrutiny. Results reported are based on either individual funds (micro level) or on those examined in aggregate (macro level), the latter being of primary concern henceforth.

Fund flows within US markets have been examined fairly extensively as a means to establish these relationships. Warther (1995) investigates aggregate equity inflows with respect to concurrent and subsequent market-wide price movements using monthly Investment Company Institute (ICI) aggregate mutual fund flow data.[1] Further to this, the fund flows are examined to determine whether they can be considered to be those of feedback or contrarian traders. The research is novel in the attempt to bridge fund flows and sentiment which is measured using the closed-end fund discount (CEFD) of Lee et al. (1990). Warther rationalises price moments in response to mutual fund flows: information revelation by such flows (directional trading based on common new information, propelling markets which results in a positive correlation), and price pressures or investor sentiment. The latter is particularly relevant here. Fund flows are alluded to as an indicator of unsophisticated investor sentiment. Should sentiment be a significant factor in financial markets, and if flows into mutual funds are indeed an appropriate measure of that sentiment, it then follows that flows into funds should have a compelling positive correlation with returns. Aggregate inflows are found to be strongly correlated with contemporaneous aggregate returns. The evidence indicates that aggregate fund flows are not positively related to past returns; the failure to detect price reversals is inconsistent with the presence of price pressures. To the contrary, flows are negatively related to past monthly returns. Thus, mutual fund investors appear to be somewhat contrarian. However, using the CEFD (noise trader sentiment measure), no such evidence was found, which either invalidates the use of the CEFD as a sentiment measure or may imply that fund flows capture a different aspect of sentiment.

Ben-Rephael, Kandel & Wohl (2010) investigate a proxy for monthly shifts between bond funds and equity funds in the US using ICI aggregate fund flow data. Their sample covers a longer period than that of Warther (1995). The derived flow measure labelled 'net exchanges' captures shifts into equity funds. It is positively contemporaneously correlated with aggregate stock market excess returns and negatively related to subsequent excess market returns. Given that net exchanges reflect asset allocation decisions between bonds and equity, the authors assume it is related to demand or supply shocks driven by economic conditions or investor sentiment. They find that net exchanges are related to stock market risk, yielding a sentiment measure which forecasts excess aggregate market returns. Thus, sentiment is then captured by examining flows between asset classes.

Investor sentiment measures beyond the direct survey-based indices tend to be illusive. The means

[1] `http://www.ici.org/`

to gauge whether mutual funds can be used as a sentiment measure are limited to exploring the time series relation to such survey results, as in Indro (2004), and the CEFD. Further studies which explore fund flows and sentiment within the US are presented in section 4.2.4. These studies are concerned exclusively with those funds domiciled within the US. Expanding the investor base (both retail and institutional) to funds domiciled globally enables further exploration to either validate or refute the use of fund flows as a sentiment measure. Due to the US being considered a dominant market force, dedicated US funds from investors domiciled globally are likely to measure global sentiment.

Fratzscher (2011) analyses cross-border fund flows to as a means to establish global capital flow determinants using a dataset provided by Emerging Portfolio Fund Research (EPFR) Global, a US-based firm that tracks the flows and allocations of funds domiciled globally. Specifically, Fratzscher examines the surge in capital flows with regards to the sub-prime crisis and finds that key events, as well as changes to global liquidity and risk, exerted a large effect on capital flows in both the crisis and recovery. The effects were heterogenous across countries, which can be explained by the strength of domestic fundamentals, country risk and differences in the quality of domestic institutions. An overall combination of 'push' and 'pull' factors were at play. 'Push' factors refer to common shocks and effect all countries whereas 'pull' factors are country-specific determinants and refer to real divergences between emerging market economies (EMEs) and advanced economies (AEs). The crisis period was marked with capital flows into bonds within developed economies whilst the recovery period was characterised by a surge of capital flows into emerging economies. The paper analyses the different drivers of global capital flows in order to establish the significance of global shocks for capital flows. A factor model is developed to distinguish between global shocks (liquidity, risks and macro news shocks) and country-specific shocks. The findings suggest it is in fact the global factors which are accountable for a large proportion of the global capital flows observed during the crisis. Comprehension of both the causes and effects of capital flows is heralded as being crucial in order to determine how future crises may pan out.

Capital is allotted to various categories of assets, most notably equities and bonds, contingent upon risk aversion as well as macroeconomic conditions. Hakkio & Keeton (2009) propose a financial stress index comprised of key variables which correspond to episodes of heightened angst in the economy. Recurring key phenomena have been associated with financial stress, the presence and relative strength thereof may differ across episodes. Increased uncertainty about the fundamental value of assets results in increased volatility in financial markets, the VIX being considered the prime 'fear gauge'. Prospective cash flows from stocks, bonds and loans all depend on future economic conditions. Thus, uncertainty about the fundamental values of these assets reflects greater uncertainty about the outlook for the economy. Another relevant indication of financial stress is a decreased willingness to hold risky financial assets as investors' risk appetite falls. Financial distress has also been associated with capital flows shifting from equity to bonds, known as the 'flight-to-quality' ('flight-to-safety') phenomenon. This change in preferences commands a higher expected return on risky assets and a lower return on safer assets (bonds).

Given that funds tend to abide by the flight-to-safety hypothesis, with the US and other advanced economies being regarded as safe-havens, global capital flows adjust to account for global macroeconomic conditions as well as country-specific factors. With regard to the US, fund flows of US-domiciled investors have been analysed to find relationships between the flows, aggregate market returns and sentiment. However, these studies have yet to incorporate capital flows into the US from non-US domiciled investors. Doing so grants access to the investment decisions of those investors which are concerned with both the US economy and associated expected returns, as well as the global macro environment and relative returns of other markets.

Research which examines how sentiment propagates to various markets is limited. Baker, Wurgler & Yuan (2011) examine whether investor sentiment is contagious across countries. They use US capital flows to the five other countries (Canada, France, Germany, Japan and the UK) to quantify the extent of integration between these markets. Based on the supposition that high sentiment forecasts low returns in the cross-section, their research affirms that sentiment is a contrarian indicator. They propose that 'countries with high absolute flows may be subject to sentiment propagation'. By virtue of the US being a dominant market force, the authors demonstrate that high US sentiment will predict negative returns to a greater extent if capital flows from the US are high. Low US sentiment is deemed to predict positive future returns to a greater extent if capital flows back to the US are high. Cross-border capital flows appear to be a channel through which sentiment propagates, further influenced by macroeconomic conditions and policies, as well as financial market conditions.

Having briefly introduced the concepts to be further explored, it is clear that sentiment with respect to a particular investor group and market is transient and contingent on the definition of sentiment. Most often, sentiment within financial markets is quantified from numerous data which include IPO activity, CEFDs, option volume ratios and equity share in new issues; it is also the case that such measures are combined to remove common information contain within all such measures (Baker & Wurgler 2006, Lemmon & Ni 2008). Thereafter, the nature of the sentiment measure is determined by inspecting the behaviour with respect to one period-ahead aggregate returns, or with that to the cross-section of returns. Most often, irrespective of frequency, sentiment is deemed contrarian. Thus, optimism precedes downwards market movements. In order to proceed, the means with which to capture sentiment within a given market is assumed to be fund flows. The current research commences with an in-depth theoretical review of related literature in an attempt to further consolidate the use of cross-border capital flows as a means to propagate sentiment (Part I). Once this has been accomplished, the assumption derived therefrom serves as the basis for the subsequent empirical section (Part II) in which the relation between global institutional investor sentiment (as measured by capital flows) and portfolio insurance is explored. Hence the question of whether global sentiment has a 'spillover' effect into US aggregate equity options markets is addressed by examining lagged relationship with related variables.

Put options are tantamount to insurance and pay off in adverse conditions; conversely, call options provide access to upside. Index options are appropriate to identify institutional investor portfolio insurance, as pessimistic perceptions of near-term aggregate equity market performance necessitates the use of put options to insure against market declines (Bates 2003). Prices of these options vary according to supply and demand, thereby resulting in the implied volatility skew for equity options since out-the-money index put options are relatively expensive. This research employs S&P 500 European index (SPX) options, as the aggregate US equity market will be represented by the underlying index. Index options markets have been considered a primary avenue wherein investor sentiment manifests (Shefrin 1999). Specifically, the risk-neutral distribution (RND) of an underlying index is essentially the market's opinion of the underlying's expected returns, adjusted for risk aversion. Option-implied skewness provides an indication of whether institutional investors are indeed concerned with market declines. Han (2007) examines whether investor sentiment about the stock market affects the prices of SPX options. Han finds that the index option volatility smile is steeper (flatter) and the risk-neutral skewness of monthly index return is more (less) negative when market sentiment becomes more bearish (bullish). The non-parametric skew is measured using the method of Bakshi et al. (2003); they demonstrate the index option volatility smile complementary to the negative skewness of the RND index return.

The method to be applied here is that of Bondarenko (2000) wherein the option-implied skew is defined as the third robust moment of the RND of the index returns, η_t^3, where t refers to the current date, and it is assumed that the nearest option maturity is selected. The daily implied skew using SPX options data over the period January 2005 to October 2010 (Chapter 3) yielded a consistent relationship to the VIX and the underlying S&P 500 index. Empirical evidence in Chapter 3 finds that an increase in the equity index tends to be accompanied by a decrease in the VIX, and an increase in the option-implied skew (it becomes less negative). Assuming that the option-implied measure may be indicative of ex ante forward-looking sentiment, we therefore exploit the information contained in SPX options. The nearest maturity will be selected (up to eight days before expiry) as sentiment is likely to impact investors' perceptions of immediate market movements more so than those with maturities thereafter. Thus, option-implied skewness can be considered another means with which to gauge investors' perceptions regarding future asset returns.

The second part of this chapter empirically explores the precise relation of institutional investor sentiment to portfolio insurance. Assuming that sentiment is propagated via capital flows (Part I) and option-implied skewness is related to institutional forward-looking sentiment, it is conceivable to expect recent positive aggregate equity fund performance to result in a contemporaneous increase in the index skew (less negative) as investors become more optimistic about near-term returns; it may also be the case that increases in bond flows are associated with a decrease in the skew (more negative) as investors become more risk averse.

In essence, we seek to establish whether global institutional investor sentiment which comprises the sentiment of both US and non-US domiciled investors, the latter being propagated via cross-border flows, is attuned to the sentiment within US options markets, and analogously, institutional portfolio insurance. Dedicated US equity and bond fund flows of both US and non-US domiciled funds from EPFR Global are employed to determine whether weekly increases in bond flows result in a decrease in the skew (Hypothesis 1) and whether this decrease is proportional to the increase that may result from recent consistent positive equity fund performance (Hypothesis 2).

This chapter is organised as follows. Part I is a purely theoretical account of the literature which seeks to substantiate the use of cross-border fund flows as a vein for sentiment propagation. Therein, section 4.2.1 discusses sentiment in relation to the macroeconomy and equity returns, section 4.2.2 discusses macroeconomic fundamentals and aggregate returns, and section 4.2.3 briefly examines the integration of financial markets. Thereafter, fund flows and their relation to aggregate market returns and investor sentiment are discussed in section 4.2.4. Part I is the justification for the assumption upon which the basis of Part II is formed.

Part II then uses the results of Part I to determine whether global institutional investor sentiment infuses into the index options market. The hypotheses are formally stated in section 4.3. Section 4.3.1 discusses the S&P 500 index European options and gives a brief account of the method to be employed to calculate the skew of the RND, section 4.3.2 details the EPFR Global fund flow dataset as well as all other financial market data to be incorporated. Monthly flow data is briefly reviewed in section 4.3.3 whilst the bulk of the empirical analysis is discussed in section 4.3.4.

Section 3.7 concludes and summarises the analysis and results.

4.2 Part I: Sentiment Propagation and Cross-Border Fund Flows

The first part of this research is a purely theoretical account of macroeconomic, sentiment and financial market integration. It draws upon various strands of finance research as a means to convincingly establish the premise on which Part II is based. That is, by referencing key ideas and empirical evidence, it appears to be the case that sentiment propagation is tantamount to cross-border capital fund flows.

4.2.1 Sentiment, the Macroeconomy and Equity Returns

Equity markets within each country represent corporate wealth and are a reflection of the robustness of the real economy to a large extent. Consumer confidence indices are an aggregation of responses to standard questions posed which reflect current and expected macroeconomic conditions as well as stock market momentum. Otoo (1999) finds that changes in US equity values are contemporaneously correlated with changes in consumer confidence using the Michigan Consumer Confidence index. Consumer confidence is Granger-caused by aggregate market returns in the

US. Increases in equity prices boost consumer confidence with a (short) lag, however the reverse does not hold. In principle, higher stock prices may boost consumption via the confidence channel. Positive stock price movements translate into more wealth and therefore increased optimism. This direct confidence effect, which is related to the traditional wealth effect, is deemed to be less important in continental Europe than in the US since European households invest a smaller share of their wealth in stocks. In addition to this, higher stock prices may be interpreted by economic agents as a sign of future favourable economic conditions. The leading indicator property of stock prices provides a channel through which equity prices may influence the behaviour of all consumers, regardless of whether they directly invest in the stock market. Granger causality from the aggregate market to confidence has also been established to hold in 11 European countries at very short horizons of two weeks to a month (Jansen & Nahuis 2003). Jansen and Nahuis find that the stock market–confidence relationship is driven by expectations about macroeconomic conditions rather than personal finances, thereby distinguishing the confidence channel from the traditional wealth effect.

Deteriorating macroeconomic data (core CPI, inflation, productivity and consumer sentiment to a large extent) for any major economy for an extended period of time leads to a deterioration in confidence. Matsusaka & Sbordone (1995) note that all recessions for the postwar period were preceded by a decline in confidence; this was seen to hold in Chapter 2 for both the US and UK. This can be interpreted as either that consumers accurately predicted recessions or that declining confidence resulted in a reduction in output. Examining the US economy between 1953 and 1988, Matsusaka and Sbordone explore the relationship between sentiment and gross national product (GNP). The uncertainty of whether confidence causes or anticipates GNP forms the basis of the vector autoregression (VAR) after controlling for fundamentals [2] and other publicly available predictors of output. They find causality running from confidence to GNP.

International evidence regarding confidence and the aggregate stock market is researched in Schmeling (2009) across 18 industrialised markets. Motivation is based on the statistically and economically significant contrarian nature of the relationship between sentiment (consumer confidence) and returns: periods of higher investor optimism tend to be followed by lower returns for the aggregate market; sentiment therefore predicts future aggregate market returns. The consumer confidence time series data is autocorrelated (highly persistent) but stationary. Con-

[2] Control variables include the Index of Leading Indicators, government expenditure, the difference in interest rate between six-month commercial paper and the six-month Treasury bill rate, termed 'default risk'.

fidence correlation coefficients are not significant. More precisely, several countries exhibited a large correlation, almost no correlation or a negative correlation. The results hold for both levels and changes of consumer confidence series. Bivariate Granger causality tests between sentiment measures and stock returns indicated a two-way 'causality': sentiment depends on previous returns and returns depend on previous sentiment movements. Higher sentiment tends to forecast lower returns. Cross-sectionally, the impact of sentiment on stock returns is higher for those countries with less market integrity and those that are culturally more prone to herd-like behaviour and over-reaction. The tests control for fundamental factors which include inflation, the annual percentage change in industrial production, the term spread, the dividend yield and the detrended (six months) short rate. Conducting panel regressions, a significantly negative relation between sentiment and returns is established, which is congruent with theoretical expectations of the impact of noise traders as well as prior empirical findings for the US. Furthermore, the effect of sentiment on average future returns declines with the forecast horizon and varies across countries. The predictive power of sentiment is most noticeable for short- and medium-term horizons of one to six months and is diluted over longer horizons of 12 to 24 months.

Thus consumer confidence has been shown to be a monthly contrarian sentiment measure of aggregate market returns. Evidence suggests that market returns Granger-cause confidence. Confidence within the US Granger-caused GNP within a VAR framework. Aggregate investors react to macro news in the near term, as can be evidenced by Ratanapakorn & Sharma (2007), thereby shifting prices away from fundamental values which revert back over time. This is explained by under- and over-reaction to earnings news in the behavioural model of Barberis, Shleifer & Vishny (1997). Consumer confidence indices are relatively low-frequency and likely unable to capture these behavioural traits. Weekly sentiment indices are therefore more suited for this purpose.

Further to consumer confidence, Fisher & Statman (2003) examine the difference between retail (small), medium and large investor sentiment survey-based measures between 1985 and 1998. Large investors are defined as Wall Street sell-side strategists; the relevant sentiment measure is compiled using monthly data from Merrill Lynch, defined as the mean allocation to stocks in their recommended portfolios. Medium investor sentiment is represented by the Investors Intelligence (II) weekly survey data from Chartcraft. The sentiment data is considered a contrarian indicator: investors are advised to sell when the proportion of bullish writers is high. Sentiment of small investors is from the American Association of Individual Investors (AAII). They further seek to establish whether investor sentiment forecasts stock returns. In particular, they investigate whether positive equity returns precede sentiment exuberance. More importantly, they hope to determine whether individual investors follow their sentiment with consistent investment action. The ramifications thereof may ultimately invalidate the use of these measures as the trades ultimately determine sentiment within financial markets.

Fisher and Statman find that the relationship between the AAII and II measures is significant over the period, whereas the relationship between the Wall Street strategists and the other two investor groups is not. Individual investors become bullish as newsletter writers become so, yet not in sync. Analysing the relationship between the level of sentiment and future returns of the S&P 500 (large cap stocks), the level of AAII and that of Wall Street strategists are reliable contrarian indicators of future S&P 500 returns: there is a negative and statistically significant relationship between the sentiment level both groups of investors and returns in the following month. Regarding monthly II data, Fisher and Statman find that the relation between the level of sentiment of newsletter writers and S&P 500 returns in the following month is negative, but not statistically significant. No evidence of a significant relationship between the change in sentiment in one month and stock returns in the subsequent month exists.

Considering that stock returns are paramount among those factors that affect sentiment, it is unclear whether momentum or reversals are expected. Fisher and Statman find a positive and statistically significant relationship between returns and future changes in II sentiment.[3] They also find a positive and statistically significant relationship between returns and changes in both II and AAII sentiment during the month. Returns had an insignificant effect on the sentiment of the Wall Street strategists. Addressing the question of whether individual investor (AAII) sentiment is in agreement with their actions, they examine the monthly AAII asset allocation survey: individual investors did follow their sentiment with investment action, as was depicted by a positive and statistically significant relationship between the monthly change in the sentiment of individual investors and the monthly change in the stock allocation in their portfolios.

Consensus regarding measures of sentiment is largely absent. The above brief review, primarily concerned with survey-based measures and in particular consumer confidence, serves as a means

[3] Clarke & Statman (1998) found that II sentiment is based on expected continuations of short-term stock returns and reversals of long-term returns.

to determine whether the aggregate attitude of those at large can be used to forecast returns. Sentiment is often viewed as a contrarian indicator. Thus high sentiment is perceived to forecast low returns, at the relevant frequency. Channels have been proposed which link consumer confidence to the stock market as a means to justify the observed relationship. Confidence is also closely related to macroeconomic data. Studies of confidence and aggregate returns which extend research globally seem to yield similar results to that within the US, albeit at varying intensities based on cultural and institutional quality as in Schmeling (2009). However, sentiment of the dominant economy (the US) is destined to affect those economies that it is both highly dependent on and integrated with. Countries are linked through capital flows and trade, both of which affect the country's financial welfare. The more fiscally secure a country appears to be and the better the fundamental macroeconomic data are, then the greater the chances of that country withstanding exogenous shocks. Ultimately, more confidence will be bestowed upon that country. This is often expressed as greater fund flows to that country as investment prospects appear favourable, contingent upon quality of financial institutions and policies. Real macroeconomic variables are indicative of the current and expected near-term state of the economy and therefore, consumer confidence is likely to capture this. Naturally, this is closely tied to the stock market of the relevant country. The following section explores the linkages between the macroeconomy and the stock market.

4.2.2 Macroeconomics and Equity Returns

There is a substantial volume of literature which endeavours to explain the relationship that exists between macro variables and equity returns. Chen & Ross (1986) examine whether certain macroeconomic variables present risks that are priced in the stock market. Specifically, they examine the spread between long and short interest rates, expected and unexpected inflation, industrial production (IP) and the spread between high- and low-grade bonds. Asset prices react to news pertaining to the economy, with some news events having a more pervasive effect than others. The comovements of asset prices suggest the presence of underlying exogenous influences.[4] Only general economic state variables will influence the pricing of stock market aggregates. Such variables have no direct impact on current cash flows yet describe the changing investment opportunity set. Unanticipated changes in the risk-free interest rate influences pricing

[4]All economic variables are endogenous in some sense. Macro variables are considered to be exogenous with the stock market being endogenous.

through the time value of future cash flows as well as the risk premium. On the demand side, changes in the indirect marginal utility of real wealth (real consumption changes) will influence pricing indirectly though unanticipated changes in risk premia. Expected cash flows change due to real and nominal forces. A change in the expected rate of inflation affects nominal expected cash flows as well as the nominal rate of interest. Innovations in the rate of productivity should have an influence on stock returns through their impact on cash flows. Using the value- and equal-weighted NYSE index, their results confirm the relevance of several economic variables in explaining expected returns, namely IP, changes in the risk premium, twists in the yield curve and more weakly, measures of unanticipated inflation as well as changes in expected inflation during periods when these variables were highly volatile. The rate of change of consumption did not seem to be significantly related to asset pricing. Hence, stock returns are exposed to systematic macroeconomic news and they are priced in accordance with their exposures.

Flannery & Protopapadakis (2002) establish which macroeconomic variables are responsible for stock price movements. Given that the data affect the future investment opportunity set or level of consumption in a non-linear and time-invariant manner, they are priced-in risk factors in equilibrium in multifactor asset pricing models. Securities affected by undiversifiable risk factors should necessarily earn risk premia in a risk-averse economy (Ross 1976). Hence macro risk factors seem to be natural candidates as they influence firms' cash flows as well as the risk-adjusted discount rate. Flannery and Protopapadakis note that the various research has yet to yield a consensus view regarding the impact of macro variables on equity returns; agreement lies in the negative impact of inflation and money growth on equity values. They estimate a GARCH model of daily equity returns in which both equity returns and their conditional volatility are allowed to vary with a range of macroeconomic series announcements from 1980 to 1996. Macroeconomic developments vary with the economy, in contrast to previous research, which thereby captures the underlying economic conditions. They identify three nominal variables (CPI, PPI, and monetary aggregate – M1 or M2) and three real variables (employment report, balance of trade and housing starts) as candidates for risk factors. Results indicated that an increase in trading volume is associated with these factors in the returns model. IP, personal income and sales did not significantly affect returns, conditional volatility or trading volume.

More recently, Ratanapakorn & Sharma (2007) examine the long-term and short-term relationships that exist between the US stock price index (S&P 500) and six macroeconomic variables over the period 1975 to 1999 using monthly data. Findings indicate that Granger causality runs from macroeconomic variables to stock prices in the long run. The selection of variables encompasses those of the money, goods, securities, and labour markets. [5] Short-term and long-term interest rates have a negative impact on stock returns since an increase in interest rates may raise financing costs, and thereby reduce future corporate profitability and stock prices. [6] The money supply [7] affects stock prices through portfolio substitution or inflationary expectation. In the case of the portfolio balance model, as suggested by the quantity theory of money, an increased money supply may re-balance other assets including securities in the portfolio. An increased supply of money may raise the discount rate through inflationary expectations, which ultimately reduces stock prices. Alternatively, an increased money supply might enhance stock prices via the liquidity effect. That is, higher liquidity in the economy reduces the interest rate, and consequently raises stock prices. Changes in the money supply lead to increased output, and since the money supply and output are positively correlated, the money supply and the stock prices have a positive relationship. Thus, the relationship between the money supply and stock prices is still uncertain. The effects of inflation on stock prices are empirically controversial. A positive relation between stock returns and inflation has been found because equity is a hedge against inflation. However, a negative relationship of stock returns to inflation is generally accepted. The quantity theory of money and money demand theory result in the negative inflation-real activity relationship. Stock returns are positively related to real variables like capital expenditures and output which then gives rise to the negative relationship. Alternatively, increased inflation may enhance the nominal risk-free rate, and ultimately the discount rate. This may then lead to a decrease in stock prices which are approximated as the discounted value of expected dividends. Earlier studies suggest that stock returns are positively related to real economic activity measured using IP. However, some studies note that asymmetric causation runs from stock returns to real economic activity, concluding that stock prices are a component of the leading economic indicators. Major stock fluctuations affect consumption, investment components and investment goods and, thus, may lead to an increase in output. Alternatively, increased output may enhance cash flows (profitability) which then results in higher stock prices.

[5] The authors note that the interest rate and the money supply represent the money market, whereas the inflation and IP represent the goods market. Both stock prices and foreign exchange rates belong to the securities market. In addition, the foreign exchange rates provide a means to explore the international effects of foreign countries on the US economy.

[6] The Treasury Bill rate and the 10-year government bond rate are reflective of the short- and long-term rates.

[7] The narrow money supply, M1, is used.

The study also considers the effects of the exchange rate. To incorporate the influence of foreign countries on the US market, the yen/dollar rate (JY) is employed to represent the foreign exchange rate. Under a free-floating exchange rate regime, the volatility of the exchange rate is greater, creating related risks. Stock-price–exchange-rate relationships are explained on different levels. According to micro foundations, changes in exchange rates may affect the value of firms' portfolios (an increase in the real dollar exchange rate serves to decrease firms' profits and, hence firms' stock prices). In the macro framework, the existence of a negative relationship between stock prices and the domestic currency is predicted. [8]

Ratanapakorn and Sharma find that all macroeconomic variables have an impact on the US stock market to some extent, suggesting that the US stock prices could be predicted by these state variables.

Interest rates are key in the stock, exchange rate and bond markets. Further examination indicated that stock prices are relatively exogenous in relation to other variables because almost 87% of its own variance is explained by its own shock even after 24 months. This implies that stock prices are more dependent on themselves than macroeconomic variables; the causality findings were such that there is no evidence of short-run causality from the stock prices to any other variables, however indirect causality runs from stock prices to the exchange rate, IP and money supply. Among six macroeconomic variables, the movement of the government bond rate seems to have the most powerful impact on the stock prices. In conclusion, under a floating exchange rate regime, Ratanapakorn and Sharma find a negative relationship between stock prices and long-term interest rates, and a positive relation between stock prices and the money supply, IP, inflation, the exchange rate and the short-term interest rate. The mixed results pertaining to interest rates may be explained by considering either the improvement in the profit outlook which increases the aggregate demand and hence investment, which thereby raises the interest rate, or that the long-term rate is more closely related to stock prices than the short-term rate. No short-run causality running from either macroeconomic variable to stock prices is found; all variables had influences on the stock price in the long run. Stock prices did Granger-cause interest rates, IP, the money supply and the exchange rate either directly or indirectly in the short run. Ratanapakorn and Sharma conclude: 'The presence of cointegration and the causality suggests

[8] Under a floating exchange rate regime, if a country is export dominant, exchange rate appreciation lowers competitiveness and negatively affects domestic stock prices. To the contrary, if a country is import dominant, exchange rate appreciation reduces input costs and creates a positive effect on domestic stock prices.

that the US stock market does not seem to be efficient. As such, future fluctuations of stock prices can be forecasted by the information set provided by the macroeconomic variables.'

A range of macroeconomic variables have been examined extensively over differing time periods. Although consensus regarding the extent to which the data affect stock prices and vice versa differs, one may conclude that key real economic data are not insignificant when forecasting index returns. The aggregate stock market is also considered a leading indicator, and although stock markets have experienced excessive depreciation in a matter of days, deviation from fundamental value in general and perceived volatility is often indicative of uncertainty regarding the future investment opportunity set which is then classified as 'sentiment'. Economies are generally not closed, and therefore it is often the case that macro data news from those countries that are closely related to the domestic economy in question will affect the stock market of the domestic economy. Specifically, the US is regarded as a dominant force globally. The following section discusses financial market and macroeconomic integration.

4.2.3 Globalisation and Integration of Financial Markets

Given the onset and development of globalisation, understanding the economic and financial linkages that exist internationally is pertinent. Macroeconomic data for any economy is not only relevant for that particular economy; its significance pertains to all those countries which have strong economic ties to the source country. The customer countries of major exporters that experience negative growth will impact the exporter country and ultimately the relevant real economy, thereby altering the macroeconomic environment.

Ammer & Mei (1996) investigate the interactions among 15 industrialised countries in the post-Bretton Woods era. They affirm that markets move in response to news regarding future dividend growth, and are correlated across countries. They examined real and financial linkages as they treat aspects of the stock market, the money market, the goods market, and the foreign exchange market in the context of a single unified system. The authors state: 'In a fully integrated economic system, labor and capital would be able to move freely across national borders. International differences in technology and production costs should vanish. Accordingly, a common shock would have a similar impact on economic growth, and thus corporate earnings and dividends, in different countries.' They rely more on financial market data than on macroeconomic data, thereby removing measurement errors. Real economic integration, and therefore the degree of financial integration of two national economies, is measured as the correlation of dividend innovations (innovations in future expected stock returns) between different countries. Financial markets that are highly integrated should yield high correlations between future expected return innovations in different countries. Variations in equity risk premia were the principal source of stock return variance in both the US and UK. Ammer and Mei also find that the US and UK real and financial economies are highly integrated, the degree of integration increased after the Bretton Woods system was abandoned: that is, since the US moved to floating rates in the early 1970s and, for the UK, the removal of exchange controls. Future dividend growth in the two countries is more highly correlated than contemporaneous output measures which is also confirmed in the multi-country application of the methodology. Thus there are lags in the international transmission of real economic shocks. Ammer and Mei conclude by stating that contemporaneous output correlations may in general understate the magnitude of real international integration.

Dickinson (2010) examines international linkages (cointegration [9] and causality) to identify the underlying economic variables which cause stock market movements as well as the impact of the US on other markets. Differences arise across different areas of the world; the US market being a primary source of movement elsewhere. In particular, Dickinson considered the extent to which correlations between international stock markets are either a result of globalisation of financial markets or are a reflection of the increasingly integrated nature of the world real economy, as represented by comovements between key macroeconomic variables. The study concentrates on the US (New York) and three European Stock markets (London, Paris and Frankfurt). Both deregulation and the appeal of portfolio diversification are cited as candidates for market integration when examined in isolation. Substantial evidence exists which suggests that stock prices are affected by a number of key macroeconomic variables. Since these macroeconomic risks will not be diversified away, market indices will be similarly affected. Hence Dickinson approaches the issue of stock index behaviour by reference to the key economic fundamentals which influence prices. Since indices may be influenced by international factors beyond those which have an impact upon the state of the domestic economy, Dickinson develops a framework which examines the extent to which the international linkages between stock indices are a result of linkages across the real economy relative to the transmission of financial disturbances. Cointegration analysis

[9] Stock market indices are non-stationary, and therefore cointegration techniques are required. Referencing previous research, Dickinson confirms the integration of markets which hold for daily, weekly and monthly market data.

yields evidence of long-run linkages between macroeconomic variables and stock indices via interest rates; this relationship appears to hold in reverse. This is agreement with Ammer & Mei (1996) who find that the stock market performance is an indicator of future economic activity. Additionally, Dickinson finds clear short-run international linkages between stock indices, thereby concluding that this may be reflective of the transmission of sentiment and not fundamentals. Thus a long-run relationship between the stock market and macroeconomy is evident, however its specific form is complex and not easily disentangled. Short-run relationships between market indices have been accounted for in terms of sentiment.

Forbes & Rigobon (2002) examine the concept of contagion of financial shocks from one market to others based on extreme comovements perceived after the fact. Such correlation coefficients are contingent upon market volatility. Thus, adjusting for this bias, they find virtually no increase in unconditional correlation during the 1997 Asian crisis, the 1994 Mexican devaluation and the 1987 US market crash. These periods of highly correlated stock market movements are considered periods of 'contagion'. This is clearly relevant to the topic of investor sentiment propagation, as panic tends to spread across borders during heightened periods of fear and uncertainty in financial crises. This is often reflected in increased market volatility. Four methods are proposed in prior research to quantify contagion: cross-market correlation coefficients which is the method applied, [10] ARCH and GARCH models, cointegration techniques [11] and direct estimation of transmission mechanisms. In the latter instance, it was found that trade linkages are important predictors of a firm's stock returns. Forbes and Rigobon define contagion as 'a significant increase in cross-market linkages after a shock to one country (or group of countries).' Thus, this refers to the instance in which cross-market comovement increases significantly after a shock to one market; it excludes comovement during periods of stability. Interdependence refers to markets which display strong linkages during all states of the world. Forbes and Rigobon acknowledge various transmission mechanisms for shocks which includes real linkages (such as trade). The focus is to measure the cross-market linkages as opposed to the propagation mechanisms (or to differentiate between them) which transmits the shocks. Their definition of contagion therefore incorporates multiple types of cross-market linkages such as the correlation in asset returns or the probability of a speculative attack. In particular, they establish that heteroscedasticity biases

[10] This method tests for correlation in returns between two markets during both stable periods and post-shock.

[11] By examining changes in the cross-market cointegrating vector over extended periods, an increase in correlations implies that international linkages have increased, possibly due to higher capital mobility or greater trade integration.

cross-correlation coefficients which are indicative of contagion in this context. After correcting for the increase in volatility, tests based on unconditional correlation do not find an increase in cross-market correlation during such crises.

Integration extends beyond financial markets. Rizova (2010) explores how gradual information diffusion occurs across the stock markets of trade-linked countries, and finds that stock market returns of a country's major customers or suppliers predict the subsequent stock market returns of that country. Trade links are established using bilateral exports and imports of goods. The economic channel which enables this predictability is from a shock to the stock market of the major customer country which subsequently predicts higher exports to that country. From July 1981 to March 2009, Rizova finds that 'a monthly strategy of buying indices of countries whose equally weighted portfolio of customers had the highest returns in the previous month and selling short indices of countries whose equally weighted portfolio of customers had the lowest returns yields an average abnormal return.' A positive shock to the stock market of a major customer results in an increase in the purchasing power of equity holders in the customer country, with the likelihood of a subsequent rise in the purchases of imported goods due to the wealth effect. An increase in financial wealth in any country is accompanied by optimism and therefore positive consumer sentiment. Hence sentiment is likely to be 'exported' by trade linkages.

The effects of macroeconomic news extends beyond stock prices to options markets. Äijö (2008) examines the effect of scheduled US and UK macroeconomic new announcements on the returns distribution of the FTSE-100 European options prices. Macroeconomic data not only affects underlying asset price movements; the content thereof clearly influences investors' perceptions of the future economic environment and market performance. Index put options are primarily used as a means to hedge such exposure by institutional investors and are clearly an effective means with which to protect against market declines. The study is relevant in that it focuses on news pertaining to not only to the domestic economy but also the US economy, which is highly influential in financial markets. Empirical results indicate that asset prices and volatilities react almost instantaneously to macroeconomic news announcements, with employment and inflationary news having the greatest impact. The consensus view is such that implied volatility tends to increase prior to the announcement and decreases thereafter as uncertainty is resolved by market participants. Considering increased market integration and the dominant role of the US, there is clearly reason to believe that both macro news pertaining to the domestic market and that of the US will effect the implied returns distribution of index options in the UK. Domestic macroeconomic variables include inflation, GDP, employment, IP and money growth. US macro variables included in the study are inflation, GDP, employment, IP and the National Association of Purchasing Management Index.

Aijo also distinguishes between the effect of good versus bad news with respect to time-to-maturity. Results indicate that volatility tends to decrease after good news and increase after bad news. Hence quality of the news is a determining factor. The entire distribution is affected by the quality of news: after bad news, implied volatility increases, skewness decreases (more left-skewed) and kurtosis decreases. The reverse is true for good news. The interpretation is that when the news is favourable, market participants attach greater weight to the possibility of positive future returns (outcomes according to the returns distribution), risks are lower and the market is more confident. This was the case for both domestic news and for news arising from the US economy. Implied volatility of the shorter maturity options were more sensitive to the news announcements. The results are consistent with the behavioural model of Barberis et al. (1997) in which good news is succeeded by good news. Hence index options can be used to gauge investor sentiment as the effects of macro news announcements, both domestic and international, are incorporated into the returns distribution. The news announcements affect the entire distribution, with shorter maturity options being more susceptible. This will be relevant in section 4.3.1 in order to justify the use of index options within the US as a means to determine whether institutional investor sentiment can be inferred therefrom and is consistent with fund flows into the US.

The above literature review is by no means exhaustive, however it does provide sufficient evidence of real and financial linkages across markets, the former due to trade and news flow and the latter due to cross-border capital flows into financial markets. To proceed, the relationship between fund flows, aggregate stock markets and sentiment within the US is summarised. Capital flow is extended to global markets, and in particular the most recent sub-prime crisis, as sentiment contagion is seemingly related to the contagion of shocks across global markets.

4.2.4 Fund Flows

Fund Flows, Returns and Sentiment

Individual and aggregate mutual fund flows have been studied as a means to capture both investor sentiment and forecast returns. Warther (1995) examines the relationship between aggregate mutual fund inflows and contemporaneous market price movements. In particular, Warther attempts to decipher whether traders follow positive feedback or contrarian strategies. Micro studies focus specifically on the allocation of capital between funds. However, at the macro level, flows between funds cancel out. It is then the aggregate flows into and out of the entire market which remain. Using monthly and weekly data published by ICI from January 1984 to December 1992, Warther separates fund flows into anticipated and unanticipated flows. The results show monthly returns to be strongly correlated with concurrent unexpected flows, yet uncorrelated with concurrent expected flows. Specifically, stock returns are correlated with flows into stock funds, and bond returns are correlated with flows into bond funds; there is little or no cross-correlation between the categories. Warther finds that returns are positively related to past flows using weekly data; the evidence disputed a positive relationship between aggregate fund flows and past returns in the weekly, monthly, quarterly, or yearly data. Thus, the results failed to find support for positive feedback strategies, in contrast to the micro studies at the individual fund level.

To determine whether sentiment affects fund flows, Warther uses the CEFD as a sentiment measure, as discussed in Lee et al. (1990) wherein results indicate that investor sentiment affects small stocks more than large stocks. Warther rationalises that 'if the relation between fund flows and returns is due to investor sentiment, then it can be argued that flows should be more strongly related to small-stock returns than to large-stock returns.' Addressing the link between aggregate fund flows and sentiment, the heightened sensitivity of small-stock returns to inflows is analysed; no convincing evidence could be found. These results extended to the relation between mutual funds and closed-end funds, implying that the oft-cited mutual funds are preferable to closed-end funds as a sentiment measure and may in fact reveal a contrasting aspect of sentiment.

Edelen & Warner (2001) examine the relation between market returns and aggregate flow into US equity funds using daily fund flows. Their study relates to the impact of an institution's trades in a stock on the stock's price, noting that such trading causes both permanent and temporary daily price effects. Their study focuses on the aggregate level over the period from February 1998 to June 1999. Daily aggregate net flows of equity mutual funds are from Daily Liquidity Trim Tabs/Heads Up Alert (TT). Flow (new subscriptions less redemptions) is reported daily and defined as the one-day percentage change in assets under management less the one-day percentage change in net asset value (NAV). Distributions are not accounted for in these data. Returns are the percentage change in the NYSE Index, excluding dividends. A positive association between aggregate daily flow and concurrent market returns can be interpreted as price impact, feedback trading (returns driving flow) or a response to information revelation. This is further addressed by Jank (2011), to be discussed below. High-frequency daily data are employed to address these issues. Examining lead–lag daily flow–return relations and also using intraday returns, Edelen and Warner conclude that flow responds to (information driving) returns, with a one-day lag. Within the trading day, the main relation appears to be that of returns responding to flow (flow-induced trades), thus implying an aggregate price impact.

Indro (2004) examines the relationship between net aggregate equity fund flow and investor sentiment using weekly flow data from AMG Data Corporation.[12] Indro seeks to determine whether mutual fund investors react to sentiment and, if so, which group of investors' sentiment can be measured using these flows. To establish the relationship between equity fund flows and market returns, Indro regresses the weekly Wilshire 5000 log-return on the percentage net aggregate equity fund flow. The results indicate that the returns are positively and significantly related to net aggregate fund flows. The fund flow in the prior two weeks also seems to affect the returns. After decomposing the flows into expected and unexpected components due to high autocorrelation present within the monthly data, the coefficient of the concurrent expected fund flow was not significantly related to the returns data whilst that of the unexpected fund flow was, at the 1% level. This indicates that higher fund flows in current and previous weeks leads to higher market returns.

Using the AAII and II weekly survey results, Indro finds that current and lagged (by one week) bullish individual investors gives rise to positive net aggregate equity fund flows. It is also the case that positive net equity flows in the current week, lead to bullish news letter writers in the following week. The relationship exists after controlling for inflation[13] and the equity risk

[12]Weekly fund flows have been collected since 1992 from 500 sources which represent 16 900 open-end mutual funds. To this date, this reflects 93% of all equity funds and 60% of net assets under management. Fund flows excluding distributions (reinvested dividends and capital gains) are used.

[13]Expected inflation is gauged using the 90-day Treasury bill. The high correlation of T-bills with expected

premium (the difference between the S&P 500 weekly return and the 10-year Treasury yield). A lagged return is also included, as investors may respond to market movements. The equity risk premium has a positive and statistically significant coefficient which indicates that an increase in the equity risk premium leads investors to move capital into equity mutual funds. Inflation has no impact on the direction of fund flows. The lagged return is also positive, which indicates positive feedback trading. Thus, equity fund investors are influenced by fundamentals as well as sentiment. Highlighting the propensity of investors to 'pour money into the stock market' as a means to propel stocks higher, Indro cites previous research (Neal & Wheatley 1998, Edelen & Warner 2001, Warther 1995) which documents the predictability of returns using fund flows. Since mutual fund investors are considered the least informed as they delegate their investment decisions to fund managers, in aggregate they are deemed suited as candidates to measure unsophisticated investor sentiment. Fund flows are usually invested or divested as a result of bullish or bearish sentiment. Warther (1995) uses the CEFD as an indirect measure of sentiment whereas the current study uses the survey-based measures, thereby linking investors' responses to their actions. Connecting investor sentiment to mutual fund flows confirms that investor behaviour associated with mutual funds is influenced by more than just economic fundamentals. Warther's results confirm that 'mutual fund investors move more money into equity funds in the current week when individual investors were more bullish the previous week. Contrary to this, a higher net aggregate equity fund flow in the current week induces newsletter writers to be more bullish the following week.' The results using the II sentiment are statistically stronger than the AAII sentiment. Thus, individual sentiment in the current or previous week is positively related to aggregate equity fund flow in the current week. Sentiment of newsletter writers in the subsequent week is positively related to net aggregate equity fund flows in the current week. Hence, mutual fund investors react to the sentiment of individual investors when investing or divesting into equity mutual funds. This trading behaviour subsequently affects the sentiment of newsletter writers (institutional investor sentiment).

Ben-Rephael et al. (2010) examine monthly ICI data which reflect flows and asset values of aggregate US mutual fund categories. They divide the fund population into two groups: the

inflation rates reflects the nature of these securities - short-term, government-guaranteed debt with virtually no credit risk. T-bills are frequently considered a 'risk-free' asset which deems them appropriate as instruments to approximate inflation. Nominal interest rates generally represent the sum of the real rate of interest and expected inflation. Cash returns (T-bills) have had a strong tendency to rise with expected inflation. Asset prices have tended to reflect consensus inflation expectations. Thus, if all investors believe future inflation will be high, then they will not be rewarded if correct (Bhardwaj et al. 2011).

equity group, which includes domestic equity, international equity and mixed funds, and the bond group, which includes bonds and money market funds. The data are divided into four categories: 'exchanges in', 'exchanges out', sales and redemptions. These combine to form the net flows. Sales and redemptions are actual cash flows which enter or exit a fund family; 'exchanges in' or 'exchanges out' are transfers between different funds in the same family. To find a value which reflects the flows between equity (funds which are either domestic or international equity or mixed funds) and bonds (all bonds and money market funds), they define 'net exchanges' as 'exchanges in' minus 'exchanges out'. This value by definition equates to zero over the all-fund population, with 'net exchanges' of equity funds being equivalent to 'net exchanges' of the bond funds, with the opposite sign. The authors exclude sales minus redemptions which are deemed to reflect long-term savings and withdrawals. Their sample covers the period of 1984–2008; Warther (1995) uses these data over a different time period and defines 'net flows' as 'net exchanges' plus sales minus redemptions, yet failed to find a relation between net aggregate monthly flows and subsequent market returns.

After normalising by fund assets, Ben-Rephael et al. find that one standard deviation of the normalised net exchanges (NEIO) is positively related to 1.95% of the excess market return. There is also a negative relation between net exchanges and subsequent excess market returns: 85% of the contemporaneous relation between excess returns are reversed within four months, the remainder within ten months. The relationship between NEIO and the VIX is negative and significant for both the level and difference. Changes in the VIX are negatively and contemporaneously correlated with excess market returns; excess market returns are not related to lagged changes in VIX. The market excess returns are positively contemporaneously related to the NEIO, followed by a reversal.

Ben-Rephael et al. rationalise the use of net exchanges as a proxy of investor sentiment since the price reversal pattern of aggregate market returns is too large to be attributed to time-varying risk premiums. Hence net exchanges are related to stock market risk. Their proposed sentiment measure appears to forecast the aggregate excess market return. Further justification to capture noise trader sentiment is that the price noise correction takes approximately 10 months. This is in agreement with the behavioural model of Shleifer & Vishny (1997) and De Long et al. (1990) which state that limits to arbitrage result in the persistence of such noise. Hence Ben-Rephael et al. specifically refer to the measurement of noise traders or retail investors.[14] NEIO is further found to be weakly negatively related to the short interest rate and weakly positively related to the consumer sentiment index of the University of Michigan Survey Center. NEIO is not related to the sentiment measure of Baker & Wurgler (2006).

Jank (2011) examines whether the concurrent relation between equity returns and mutual funds can be explained by macroeconomic news. Several explanations of the results in Warther (1995) (positive returns generate flow) have been proposed: the *feedback trader hypothesis* which implies that returns cause fund flows since rising prices may yield more purchases. Alternatively, the causality can be explained in reverse: the *price pressure hypothesis* justifies higher prices resulting from sentiment-based demand for stocks (optimism or pessimism unrelated to fundamentals), thereby rendering mutual fund flows a sentiment measure. The author attempts to prove the *information response hypothesis* which states that both stock market returns and fund flows together react to new information about the real economy. Under the price pressure hypothesis and the information response hypothesis, the mutual fund investors' demand for equity, hence fund flows, fluctuates. The crucial difference is that in case of the price pressure hypothesis, fund flows are unrelated to fundamentals. In contrast to this, preferences within the information response hypothesis are driven by fundamentals pertaining to the real economy.

Given that the stock market responds to business cycles which can be seen from time-varying expected returns as well as equity risk premia, recessions necessitate higher expected returns as a means to compensate for higher risk. Hence, information pertaining to the macroeconomy will ultimately affect the perceived risk in holding certain stocks, thereby inducing mutual fund flows to react to price adjustments from news content. Positive news leads to an increase in prices, and ultimately flows into mutual funds. Jank examines the link between aggregate mutual fund flows, time-varying equity premium and asset prices. Mutual fund investors are retail investors, and therefore have different preferences since they are more risk averse than other investors, and are less willing to hold equity in adverse economic conditions. They might also have a higher exposure to idiosyncratic income shocks than other private or institutional investors. The hypothesis tests whether changes in news variables, which reflect higher risk and thus a higher equity premium, should result in outflows from equity funds. If fund flows and market returns react to like news about the real economy, then mutual fund flows and stock market returns might possibly both

[14] In 2007, 86% of mutual fund assets were held by retail investors.

predict economic activity. Specifically, if mutual fund flows react to developments within the real economy, then such flows should necessarily predict real economic activity.

Examining monthly data from ICI, [15] the results indicate that mutual fund flows do indeed react to variables that forecast the equity premium and the dividend yield[16]. Changes in the dividend–price ratio explain fund flows beyond the information contained in returns. The market return is proxied by the return of the S&P 500. An increase in default spread (the end-of-period difference between Moody's BAA and AAA Seasoned Corporate Bond Yield) or consumption–wealth ratio, both indicating a rise in equity premium, leads to mutual fund outflows; an increase in the relative T-Bill rate (the three-month T-Bill rate minus its 12-month moving average), indicating a decrease in equity premium, leads to inflows into equity funds. If mutual fund investors are on average correct regarding the future state of the economy, then those variables indicative of this state should deteriorate after outflows and improve after inflows. To test this hypothesis, a bivariate VAR framework of mutual fund flows and economic activity growth is explored. Empirical results indicate that mutual fund flows predict future economic activity as measured by real GDP, IP, consumption and labour income. These findings support the theory that market returns and mutual fund flows simultaneously react to macroeconomic news.

Given that Jank provides evidence linking the real economy with mutual fund flows, which are induced by the decisions of private (retail) investors, one can further conclude that fundamentals as well as sentiment appear to be a determining factor of fund flows. Consumer confidence has been shown to reflect past stock market performance as well as forecast future macroeconomic variables. Those individuals that partake in mutual fund trading activity are not mutually exclusive from those that are representative of confidence within the economy. Hence the positive relationship between stock market returns and mutual fund flows (the unexpected component thereof in Warther (1995)), may be reflective of past good performance as well as a response to macroeconomic news. Sentiment is often associated with trading decisions which are not based on fundamentals and is responsible for the difference between the observed price of an asset and its fundamental value. Given the positive and significant relationship with excess market returns, the reversal being too great to be justified by a time-varying risk premium, mutual fund flows

[15] Following Warther (1995), quarterly net flows are calculated as new sales minus redemptions plus exchanges-in minus exchanges-out; this is then standardised by the total market value of the previous quarter using the total market index from Thomson Reuters Datastream. Fund flows are measured over the period of one quarter in order to link them to macroeconomic data.

[16] The dividend yield of the S&P 500 is measured by the ratio of average annual dividends and end-of-quarter prices, taken in logs.

are thereby believed to be a suitable sentiment measure. Contingent on the dataset, this may pertain to either retail or institutional investors. The shifts between bond and equity funds are also related to excess market returns and deemed a contrarian sentiment measure. Ultimately, variables derived from aggregate fund flows are clearly related to stock market returns, real economic activity and investor sentiment. Concluding that capital flows do capture the sentiment of those investors, it then is not inconceivable that cross-border capital flows are a conduit for sentiment propagation.

Baker et al. (2011) explore the idea of sentiment contagion based on US capital flows to a selection of developed markets, namely Canada, France, Germany, Japan and the UK. Indices of investor sentiment for each country are initially formed using the first principal component of several time series proxies for sentiment.[17] These are further decomposed into a global and six local indices, based on the methodology of Baker & Wurgler (2004). Their premise is such that if sentiment drives prices too far from fundamental value, corrections may be observed to manifest in return predictability.

Baker et al. find that total sentiment, and particularly the global component thereof, is a contrarian predictor of country-level market returns. When a country's total sentiment is high, future returns are relatively low for its small, high-return volatility, growth, and distressed stocks. This is intuitive since global investors which seek diversification tend to invest in index funds rather than specific international stocks; domestic investors are also biased toward their local markets[18] and can trade at lower costs than international investors. Empirically, not only do their measures of local and global sentiment predict returns, but also that of the US which is linked by capital flows. They allude to capital flows as being a key mechanism through which global sentiment develops and propagates.

Having established that high global and local sentiment forecasts low returns, Baker et al. conclude that global sentiment may be contagious. Either investors in the source country (from whence the capital originates) are optimistic about the local (receiver country) investment prospects and economy at large, or the sentiment within the source country is optimistic and spills over into receiver countries, thereby increasing their shares of risky assets. In the first instance, an

[17] Validation of their indices is based on dual-listed shares; these shares are pairs of securities that claim equal cash flows but trade in different markets and sometimes at substantially different prices. They find that the shares' relative prices are positively related to the relative local sentiment indices of their respective markets.

[18] French & Poterba (1991) note that cross-border investment is growing. Given the date of publication, the results are likely not applicable.

appreciation of local sentiment will be seen instantaneously, as asset prices tend to increase. In the second instance, the optimism in the source country will lead to an increase in the local sentiment via capital flows, after the shares of risky assets are bid up. The authors hypothesise that countries with high absolute flows will be subject to sentiment propagation.

Fund flows are determined by the collective trading behaviour of the individuals of the reference group. Pertaining to micro differences in investor behaviour, Finucane, Slovic, Mertz, Flynn & Satterfield (2000) discuss the social/cultural argument with respect to gender differences in risk taking. They examine how gender and race are related to a range of sociopolitical factors thought to influence risk perceptions. Their data suggest that general attitudes toward the world and its social organisation and stigma are different for white males compared with other groups. Olsen & Cox (2001) documented that cultural factors had non-trivial effects on how assets were managed; investment managers made different decisions based on identifiable cultural differences, even with equivalent training, experience and information. Cultural differences may be largely responsible for differences in investor behaviour. Thus, counties are subject to investor sentiment as financial market participants exhibit biases and therefore, exhibit specific trading patterns. Sentiment propagation is determined on a macro level due to fundamentals and aggregate performance yet it is the accumulation of those country-specific investors which determine the fate of fund flows. Fund flows within the US have been examined at varying frequencies using different datasets in order to quantify sentiment and explain the relation to market returns and fundamentals. Examining cross-border flows, the following sections present research which make use of the EPFR Global dataset. In particular, a factor model is developed to discern global capital flow determinants. Thereafter, the flow–returns relationship evident in previous research is extended across regions and countries – relative flow information is examined as a means to forecast returns.

Global Capital Flows

Examining the EPFR global database for 50 countries, [19] Fratzscher (2011) examines heterogeneity of flows across regions and time periods in an attempt to understand whether common or idiosyncratic shocks were largely responsible for observed flows during the sub-prime crisis. This dataset will be further discussed in Part II, section 4.3.2. Given the imbalance in trade and

[19] The EPFR portfolio flows and those stemming from total balance-of-payments data have been shown to match convincingly.

capital flows in deficit countries, most notably the US, prior to the latest financial crisis (2007–2009), Fratzscher asserts that many observers believed that an adjustment would be achieved through a reduction in capital flows as well as a fall in asset prices and exchange rates. However, capital flows into the US during the crisis period were largely unaffected. During the recovery period, a large portion of portfolio flows were directed at EMEs, thereby raising concerns about the respective domestic economy, capital and exchange rate markets. Examining stylised facts of high-frequency (weekly) capital flows during the crisis, Fratzscher finds that on aggregate advanced economies (AEs) experienced net capital outflows from the start of the crisis in August 2007[20] which slowed after the collapse of Lehman Brothers in September 2008. Net portfolio flows to emerging market economies (EMEs) were largely unaffected as net inflows were positive at the beginning of the crisis through July 2008. They then dropped substantially after the collapse of Lehman Brothers, up to early 2009.

There was a divergence of net flows between equities and bonds; the latter underwent much larger swings as the Lehman event triggered substantial outflows out of EME bonds (30% excluding valuation changes over a period of 4–5 months). Equities throughout were relatively stable; EME equities declined slightly following the Lehman event but recovered strongly in 2009 along with the EME bonds. Among AEs, the US experienced very little change in either equity or bond flows during the height of the crisis. The AEs in the Euro area experienced major outflows, particularly from bonds. EM Europe experienced the strongest outflows in both bonds and equities, amongst the EMEs and recovered slowest. Latin American economies did not fare much better. Fratzscher notes that cross-country heterogeneity or dispersion in net capital flows (the standard deviation of weekly net capital flows across countries over a centred moving window of six months) was vastly different for AEs and EMEs. In particular, dispersion amongst advanced Europe and other AEs was not particularly high during the height of the crisis; this is in contrast to the EMEs. Following the 2007–2008 crisis, there has been a substantial net capital inflow to the EMEs since April 2009. The total assets under management, net of valuation changes (AUM), for both equities and bonds in late 2010 exceeded both those before the crisis. Most notably, in the early period of the 2007–2008 crisis, most advanced economies experienced net outflows whilst EMEs recorded balanced flows into the summer of 2008. The collapse of Lehman resulted in capital repatriating to the US and some advanced economies after exiting EMEs; this was stronger for bond flows than for equity flows. Secondly, heterogeneity increased across countries

[20]The start of the liquidity crunch is dated 7 August 2007.

during the height of the financial crisis.

The empirical examination pertaining to the global dynamics of capital flows during the crisis and the heterogeneity thereof is captured in a factor model using weekly flows. This is to determine whether portfolio capital flows reflect common (global) shocks and/or idiosyncratic (domestic) shocks, aiding the comprehension of the overall drivers and transmission channels of the crisis. Net capital flows are aggregated at the level of the recipient country at the aforementioned frequency between October 2005 to November 2010. Doing so alleviates any uncertainty regarding different trading times of various regions of daily data which may have arisen from shocks; weekly data is also preferred to monthly data as the effects of specific events are harder to identify. The analysis aggregates equities, the dominant holding, and bonds. The US represents the majority of the equity and bond portfolios.[21] A set of global and common shocks are incorporated as factors. The US is a recipient country of capital and therefore excluded from all model estimations. Most of the common shocks are therefore US macroeconomic news variables, expressed as a composite measure. US (and domestic) equity market returns are specifically included due to their asserted relationship. The results indicate that only EMEs experienced a negative effect from crisis events. Worsening liquidity, as measured by a rise in the TED spread (the difference between the three-month T-bill interest rate and three-month LIBOR), induces net portfolio outflows. The effect thereof was dampened during the crisis period. The response to changes in global risk as proxied by the VIX, yields heterogeneity across countries during the crisis at heightened risk levels. Prior to the crisis, a rise in the VIX led to outflows from AEs to EMEs. During the crisis, the sharp increase in global risk induced net inflows to AEs and outflows out of EMEs. This is indicative of the 'flight-to-safety' phenomenon as a key driver of capital flows.

During non-crisis periods, Fratzscher finds that a positive US macro shock induces capital outflows from the domestic economy as capital is repatriated back to the US, whilst a positive domestic macro shock results in net capital inflows. During the crisis period, the sign for domestic macro shocks changes in the crisis for AEs: negative domestic shocks triggered net capital outflows out of EMEs and net inflows into AEs (a repatriation of capital from abroad of investors based in the AEs), thereby conforming to the flight-to-safety hypothesis. Positive US equity and domestic equity returns resulted in greater net capital inflows during both non-crisis and crisis periods.

[21]The total net assets recorded at 31 December 2010 stood at 1768 654.07 and 934 699.52 billions of USD respectively.

There is a sensitivity of flows to crisis events: crisis events triggered capital outflows of equities in both AEs and EMEs, as well as EME bonds, but induced net inflows into AE bonds. It was also found that an increase in risk during the crisis led to a strong response of net outflows of EME bonds into some AE equities. EME bonds appeared to be far more sensitive to these shocks (including TED spreads) as can be seen by larger net outflows. Having restricted the analysis to the post-Lehman period between September 2008 to March 2009 for robustness, it was found that net total capital outflows were sharpest (out of EMEs in particular) as a result of sensitivity to both common and idiosyncratic shock. The coefficients to liquidity shocks (TED spread) were higher in this period. Correlation coefficients for all common and idiosyncratic shocks between crisis and non-crisis periods were negative: countries with large negative coefficients for risk shocks in the non-crisis period were those with the least negative or positive coefficients during the crisis period. Hence countries which were sensitive to common shocks prior to the crisis saw the sharpest reductions or reversals during the crisis.

Extending the analysis to the European sovereign debt crisis in 2009, and the issue of whether the increase in flows to EMEs were due to push (global or common) or pull (domestic) factors, Fratzscher found that those events pertaining to the crisis had not affected the flows. In conclusion, the flight-to-safety phenomenon characterised global capital flows during the 2007–2008 financial crisis, with global shocks having exerted a large effect on EMEs. Country-specific institutions and fundamentals were largely responsible for heterogeneity of capital flows. Those countries which display strong macroeconomic fundamentals and a high institutional quality insulated themselves from common and idiosyncratic shocks. External exposure through finance and trade appears to have played a minor role for cross-country differences in the transmission of global shocks. Examining the economic significance of push versus pull factors over the 2005–2010 period, it was found that both had equal importance. However from 2009 onwards, the pull factors were slightly more important for EMEs in Latin America and Asia in the 2009–2010 capital flows to the EME region. Common factors accounted for roughly 73% of global net capital flows during the crisis.

Predictive Returns

Meyer et al. (2006) seek to establish the predictive ability of weekly flow data using the EPFR Global database regarding the relative performance of regions. Fund flow data is expressed as a percentage of total assets as this allows for a clearer comparison between regions. Funds investing in EMEs tend to be smaller than those investing in developed markets such that weekly flows in dollar terms do not accurately reflect the flow momentum across regions. Flows in US dollars are also dependant on foreign exchange movements. As the dollar strengthens or weakens relative to the funds' respective local currencies, fluctuations in the overall funds are not necessarily the result of equity investor behaviour. The fund flow data for both AEs and EMEs did not display seasonality. Since fund flows should positively impact performance and positive performance should attract fund flows, inertia in fund flows is expected. Autocorrelation of fund flows on a weekly basis was found to be high: inflows or outflows in any one week seem likely to be followed by inflows or outflows in the following week thereby suggesting that fund flows can be used as a gauge of investor sentiment.[22] Meyer et al. also find that correlations are positive in general, even between International Bond funds, the safest asset class, and EME equity funds, the most risky asset class. These results hold true for one-week flows as well as for average four-week flows. Remarkably, US equities are the only fund class for which the flows seem to be uncorrelated with other flows.

Meyer et al. then examine whether knowledge of fund flows can be used to account for equity market performance. In particular, they seek to determine whether the change in the direction of the fund flows is an indicator for subsequent performance and can be used in trading strategies. A comparison between the fund flow data and the performance of the relevant MSCI indices[23] is made in order to establish the possibility of predictability. The total global weekly equity flows as percentage of NAV as well as the global four-week moving average of these flows, are compared to the global MSCI Equity Index. The global data is an aggregation of all the flows across the regions in the universe. They find that a rising equity market index is strongly correlated with inflows and vice versa. This relationship is particularly strong in the fund flows of Europe, GEM (general emerging markets), the US and Japan. A strong positive correlation between performance as given by the relevant MSCI index and lagged fund flows exists, providing clear evidence that performance attracts flows. Even with a two-week lag, flows tend to follow performance. Flows do not appear to lead performance in the following weeks. Thus, there is a concrete relationship between equity market performance and fund flows.

[22] According to the analysis, the highest first-order autocorrelation was for funds investing in EMEA equities, with a correlation coefficient of 0.54, compared to an average of 0.27.

[23] `http://www.msci.com/`

The direction of fund flows in a rising market yields incorrect signals on average, indicating that a simple long–short strategy based on lagged weekly flows is not successful. They define the 'liquidity pulse' as a measure of rising or contracting liquidity, which compares the size of the current flow (four-week average as % of NAV) to the average size of the flow in the last 13 weeks. The relative size is given in standard deviation from the mean. Flows might still be positive (negative) yet the size of the inflows (outflows) might be dropping off, indicating a declining (rising) investor conviction or sentiment. An increase in this value tends to be associated with a strong performance of the asset class. Common trends can be perceived when comparing liquidity pulse data with equity performance. Trends of the US liquidity pulse versus the US MSCI equity index performance from April 2004 to July 2006 are similar during periods of consistent liquidity momentum expansion and contraction. Thus fund flows are a momentum indicator. However, if liquidity momentum is signalled to be very strong (or very weak) the subsequent performance tends to be negative (or positive). This suggests that the liquidity pulse becomes a contra-indicator when momentum has become too strong in either direction. These contradictory results are applicable to other regions. Using the liquidity measure with one-week and the four-week moving average as a % of NAV was inconclusive, mainly due to historical limits to the dataset, and was especially poor during bull markets. A cross-sectional analysis shows that the relative strength of fund flows for different regions contains explanatory power for subsequent relative performance of the regions, thereby adding value to models of regional equity allocation.

This is a brief account of the usefulness of cross-border fund flows as a means to forecast relative aggregate equity market performance. Monitoring flows is insightful as one may monitor high-frequency investment decisions based on global and domestic fundamentals as well as sentiment. Investors' risk profiles are paramount to the execution of these decisions. Yet, to disentangle relationships between fund flows, fundamentals and sentiment is complex. At best, identification of the push versus pull factors which dictate the allocation of capital according to asset class and fund type/geographic sheds some light on this topic. However, it is also clear that investors chase performance and allocate funds to those economies and asset classes that are favourable in this respect. Sentiment is tantamount to active investment decisions based on fund flows. Given that fund flows are considered sentiment measures, it follows that cross-border flows are the means by which sentiment propagates. Part II is the empirical section which determines whether global sentiment and portfolio insurance are aligned.

4.3 Part II: Empirical Results

Part I of this chapter has covered a broad range of literature, amalgamating empirical results which link the macroeconomy, financial markets, confidence and fund flows. The integration of economies, and in particular that of financial markets, leads to the flow of sentiment within the reference domestic economy to all those that are associated with it. This high-frequency process, herein referred to as *sentiment propagation*, occurs via cross-border capital flows. The US is considered a dominant economy and therefore associated flows are a global measure of sentiment.

This part of the research means to establish whether portfolio insurance and institutional investor sentiment coincide. The main results are addressed in section 4.3.4. The hypotheses are as follows:

- Hypothesis 1: Increases in institutional dedicated US bond flows signal a decrease in the aggregate market skew;
- Hypothesis 2: Positive equity fund performance leads to (or is accompanied by) an increase in the skew.

The section begins with a review of institutional portfolio insurance. Thereafter, data are discussed in section 4.3.2. The empirical analysis begins with a brief review of monthly flows and performance in section 4.3.3. The majority of the analysis is performed using weekly flows. Given that common global shocks are captured using the VIX and TED spread in Fratzscher (2011), these variables are on occasion included within the analysis. Section 4.3.4 examines time series properties of flows and performance as well as examines the relationship to the II bull–bear spread. Thereafter, the option-implied skew is analysed and regressed on relevant time series to establish or refute the hypotheses.

4.3.1 Portfolio Insurance – SPX Options

Index options insure against aggregate market declines. Henceforth, the S&P 500 total returns index will represent the aggregate US equity market. Volatility is that input parameter into the Black–Scholes option pricing formula (Black & Scholes 1973) which in theory should be the same for all options of a given maturity. However, observed prices can be used to obtain the implied volatility by inverting the option pricing formula. Doing so results in a ‘volatility smile’ as the parameter varies according to strike for each maturity of options available. The option-implied volatility skew/smile has been a much-debated topic, leading to a plethora of research which seeks to model the underlying price process and find a more suitable returns distribution than that of the log-normal distribution. Using European options data to extract a RND has been employed to determine the probability of attaining a certain return at that specific expiry, given current market conditions. Shefrin (1999) notes that option markets are likely conduits for investor sentiment. Quantifying heterogeneity of opinions using the call–put option volume ratio (CPR), [24] the author finds differences when compared to the survey-based measured of AAII and II (the ratio of bullish investors to the sum of bullish plus bearish investors). A high CPR has been associated with positive investor sentiment. A salient market trend which is tantamount to 'irrational exuberance', often yields divergent opinions amongst individual and professional investors; the former predict continuation whereas the latter forecast a reversal. Examining the movements post Greenspan's speech (5 December 1996) [25], it was the CPR which was in decline prior to as well as after, indicating a movement into puts. Each SPX contract is for 250 times the value of the index, hence institutional investors' heterogeneity of beliefs can be quantified using these index options. The AAII and II indices were both bullish in November 1996 as the market soared, although newsletter writers increasingly believed a correction to be due. Options markets clearly incorporate the sentiment regarding future market movements more immediately than survey measures.

Bollen & Whaley (2004) find a transitory positive relationship between changes in the level of an option's implied volatility and the time variation in demand for the option. With an upward sloping supply curve, implied volatility will exceed actual return volatility – the difference is due to costs associated with the hedging portfolio or risk exposure. Their overall results suggest that net buying pressure is an important determinant of the shape of the implied volatility function, particularly for SPX options where public order imbalances are greatest. Therefore, prices of SPX options will fluctuate as demand and supply varies. Since there are no natural counter-parties, market makers absorb the imbalance.

The premise is such that institutional investor portfolio insurance requirements render the index returns distribution negatively skewed. Options markets have been shown to react to macro news.

[24] The put–call ratio is the ratio of open daily call-option volume to open daily put-option volume aggregated across all exchange-traded options in the US.

[25] `http://www.federalreserve.gov/boarddocs/speeches/1996/19961205.htm`

Fund flows are also susceptible to the global (US) as well as domestic fundamental factors. Hence one should expect global sentiment to be present within US index option markets. Sentiment research has yet to examine dedicated US equity and bond flows for all domiciled investors. These funds assimilate both US and non-US investors' perceptions of global macroeconomic conditions, as measured by such capital flows. The CBOE VIX is based on the 30-day implied volatility of SPX options and is one of the global shocks, along with liquidity which is gauged from the TED spread, to affect cross-border capital flows. Therefore, the inclusion of options data may be crucial to consolidate evidence linking mutual fund flows to investor sentiment. With reference to SPX options, institutional investors buy index puts as portfolio insurance; bearish investors will pay more for state contingent claims that pay off when the index level is low. A shift from equity to bonds or an increase in the absolute level of bond holdings is associated with a flight-to-safety. It follows that an increase in US bond flows should result in a decreased skew. Positive performance of equity funds which is generally associated with positive aggregate market performance, should result in an increase in the skew. This forms the basis of the empirical section.

In order to proceed, the method of Bondarenko (2000) is applied to the nearest maturity European options as they tend to be most affected by macro news. Details describing this procedure is in Chapter 3. After having estimated the returns RND, the third robust moment or equivalently the risk-neutral skew is calculated. This measure is fairly intuitive as it is a 'crude' measure of the mass of the distribution:

$$\eta_t^3 = \frac{(U_{90} - U_{50}) - (U_{50} - U_{10})}{U_{90} - U_{10}},$$

where U_{50} is the median of the return distribution and, in general, U_x is the xth percentile of the returns distribution. Bondarenko finds a time series relationship between η_t^3 and both past and contemporaneous daily returns. Having estimated the RND using positive convolution approximation, results indicate that the index return is positively related to the third robust moment. When the index advances, η_t^3 becomes less negative. Since the RND is determined by investors' subjective probability of the asset's future returns as well as their risk preferences, investors' beliefs as well as attitude towards risk may vary in response to the recent index movement. Thus, decreases in the index may results in a less optimistic (pessimistic) market and investors' may become more risk averse in the near future. This may warrant a demand for more portfolio insurance (contracts which pay off in unfavourable states of the world) which leads to fatter left tails of the RND. To the contrary, recent good performance may result in less risk aversion and a higher degree of optimism. Hence the implied RND will be less skewed. Thus, η_t^3 should be less negative which results in a greater proportion of the probability to the right of the mean.

The following section begins with a description of the fund flows dataset. Thereafter, the data required to find η_t^3 are explored, along with the remaining sentiment variables that will be used to further support or refute the findings.

4.3.2 Data Selection

Fund Flow Data

EPFR Global provides access to institutional and individual investor flows and fund performance data which are sourced directly from fund managers and administrators. The universe covers over $15 trillion in globally domiciled funds. Flows are available at the asset class aggregate, fund group, investment manager, individual fund or share class levels. Datasets are either core (direct from the source) or derived; the latter is based on flows and allocations data. The core datasets are the Fund Flows: the amount of cash flowing into and out of funds world-wide, and Fund Allocations: fund manager allocations at month-end across the countries or sectors they invest in. These are combined to give rise to the derived dataset, Country and Sector Flows: distribution of fund flows by country or sector. Fund types can be further dissimilated according to the following:

– asset class: dedicated country funds versus global, general emerging market (GEM), and regional mandates;

– investor type: institutional versus retail, US domiciled versus non-US domiciled;

– fund type: mutual funds versus ETFs, active versus passive.

The prospectus/fact sheet determines whether a fund is actively or passively managed. The fund's mandate is specified therein, which may be to follow a particular benchmark or index. Passive funds may have a small turnover (10–15% annually) to adjust for indices being updated with new companies/stocks. For the split between retail versus institutional flow, EPFR Global follows three guidelines. Institutional funds fulfil the following:

– minimum entry to gain access into the fund is at least 100 000 USD;

– share class - if it is an institutional share;

– prospectus confirms the fund's main target audience.

All ETFs are regarded as institutional; since ETF share creation units typically start at 1 million USD, the creation units themselves are only sold to institutional investors. They do not track secondary market trading activity in ETFs.

The flow percentage is derived by dividing flow over the week by assets in the start of the period. The Fund Flow (FF) Dataset is the primary source of data to be used. The Country Flow (CF) dataset combines the FF and country weightings (CW) data to track the flow of money into world stock markets. The FF reports track the amount of cash flowing into and out of investment funds that are monitored globally. The CW report tracks monthly fund manager allocations across the various markets they invest in. At each month-end, the average manager weighting for each of the fund groups that can invest in the reference country is then the country weighting (allocation). Thus, the fund flow (at the required frequency) multiplied by the country allocation yields the country flow. For dedicated country funds, 100% of the allocation is invested in the reference country.

The FF dataset – tracks daily, weekly and monthly data:

– equity, bond and specialty fund groups;

– calculate net flows (investor contributions/redemptions) for individual funds and for various fund groups;

– net flows calculations exclude portfolio performance and currency fluctuations;

– data is organised by fund group;

– covers funds registered for sale in most major developed market jurisdictions and offshore domiciles, including USA, UK, Canada, Luxembourg, Switzerland, Australia, Hong Kong, Channel Islands, Germany, Austria, France and others.

– historical data shows daily/weekly/monthly aggregate flows by fund group.

The CF dataset – tracks daily, weekly and monthly data:

– equity and bond fund groups;

– data tracks the flow of money into and out of world stock markets;

– combines FF and country allocations data to estimate the flow of cash into and out of various stock markets;

– for equity funds, covers 104 emerging and developed markets;

– for bond funds, covers 108 emerging and developed markets;

– historical data shows daily/weekly/monthly aggregate flows by fund group.

The weekly data are measured from Thursday to Wednesday, with the data released on Thursday at 16:00 ET. So the lag is one day (T+1). The variables which are of specific interest are fund flows (measured in millions of USD) expressed as a percentage of NAV. The fund flows are defined as

$$\text{Fund Flows} = \text{End of Week Assets - Beginning of Week Assets - Portfolio Change.}$$

Net flow calculations exclude portfolio performance and currency fluctuations. Percent change in NAV is defined as the return on assets (performance). The portfolio change is calculated as the beginning of week assets multiplied by the NAV performance. To further clarify,

$$\begin{aligned}\text{Change in Net Asset Value} &= \text{Change in Total Net Assets} - \text{Net Flow} - \text{FX effect},\\ \text{Net Fund Flows} &= \text{Change in Total Net Assets} - \text{Change in Net Asset Value}.\end{aligned}$$

The total net assets (TNA) is recorded at the start of the period. For the CF dataset, we have that

$$\text{Estimated Allocation} = \text{Total Net Assets} \times \text{Country Allocation}.$$

For dedicated country funds, the country allocation is 100% and TNA equates to the estimated allocation in USD. New allocation data is released on the 23rd of each month; hence CFs will normally be impacted after the 23rd of the month. Weekly institutional and retail flows of dedicated USA equity and bond funds[26] over the period January 2005 to December 2010 are analysed. These flows (FF core dataset) are the sum of US and non-US domiciled investors. With regard to portfolio insurance, the analysis is restricted to institutional investors. The following section briefly discusses monthly flows, presenting a graphical depiction thereof which is accompanied by summary statistics. Further to this, correlation coefficients for monthly US benchmark data are provided: the University of Michigan consumer confidence index, The Conference Board leading economic indicator and the ISM purchasing managers index.

Financial Market and Sentiment Data

The total S&P 500 represents the aggregate equity market – the best single gauge of large cap US equities.[27] The fund flow portfolio performance includes dividends, and therefore the total returns index is used. The total return index of the S&P 500, the TED spread, and the CBOE VIX are obtained from DataStream; the weekly data are on the last business day of each week (Friday). II and AAII survey data are released on Tuesday of the week. The bull–bear spread for both II and AAII is the difference between bullish and bearish investor opinions, expressed as a percentage, of any given week. The SPX options data and US risk-free yield curve are obtained from OptionMetrics, Wharton Research Data Services. SPX options which trade on the Chicago Board Options Exchange (CBOE) are one of the most actively traded European index options worldwide. The risk-free rate is approximated (linearly interpolated) using Treasury bill rates from the yield curve. For any given maturity, there are usually more options traded below the current spot level than above, implying that options contain more information about the left tail than the right. Out-the-money options are more liquid than in-the-money options and puts are more liquid than calls. The following exclusion filters are applied to the data when calculating the RND to avoid any micro-structure related bias:

[26] All Bond Funds can be further dissimilated into Long Term Bond Funds, Long Term Corporate Funds, Long Term Government Funds, Mortgage Backed Funds, Municipal Bond Funds, Short Term Bond Funds, Short Term Corporate Funds, Short Term Government Funds, Total Return Funds, All Emerging Markets Funds (local, hard, blend currency funds), Floating Rate Funds, High Yield Funds, Inflation Protected Funds, Intermediate Term Corporate Funds, Intermediate Term Funds, and Intermediate Term Government Funds.

[27] `http://www.standardandpoors.com/indices/sp-500/en/us/?indexId=spusa-500-usduf--p-us-l--`

- Eliminate options with zero trading volume and prices below 1/8 (this is the average of the bid and ask);
- Eliminate options with extreme far-from-the-money strikes if they are separated from the main group of strikes by 25 points or more;
- Eliminate all options with maturities of eight days or less.

In order to estimate η_t^3 where t refers to the current date (week), the third robust moment of Bondarenko (2000) is estimated for daily data and averaged from Monday to Friday of the relevant week t. Further details are in Chapter 3.

Notation

With regard to notation, $ff_{x,t}^{y}$ refers to the monthly/weekly FF dedicated USA fund flows expressed as a percentage of NAV for a given month/week t, where y refers to asset class as either equity or bond $y = e,\ b$ respectively, and x indicates which group of investor flows are being examined. That is, $x = i$ or r where i refers to institutional investors and r refers to retail investors for the combined US and non-US domiciled funds. CC refers to the University of Michigan consumer confidence index, LEI denotes the Conference Board leading economic indicator and PSM is then the ISM purchasing managers index. All flows over the week are expressed as a percentage of NAV (as of the beginning of the week). The percentage change in NAV over the week is also examined with respect to flows as a measure of fund performance. This is denoted as $_{N}ff_{x,t}^{y}$. II refers to the bull–bear spread. AAII is analogous to the bull–bear spread, however it refers to individual (retail) investor sentiment. The aggregate market weekly return R_t is given by

$$R_t \quad = \quad 100 \cdot \ln \frac{S_t}{S_{t-1}},$$

where S_t is the total returns index level of the S&P 500 on the Friday of week t.

4.3.3 Monthly Flows

This section briefly examines monthly $ff^e_{i,t}$, $ff^e_{r,t}$, $ff^b_{i,t}$ and $ff^b_{r,t}$, expressed as a percentage of NAV. The data are taken between January 2005 and December 2010. Summary statistics in Table 4.1 and time series properties for the fund flows are provided. The correlation of these time series with the three indices CC, LEI and PMI are also provided in Table 4.2. This is a rough indication of whether fund flows are attuned to confidence and the macro PMI. The summary statistics are for 72 monthly observations of fund flow data expressed as a percentage of NAV. Institutional investors have a much higher average flow into bonds as well as equities. On average, retail investors seem to have withdrawn capital from equities. Jarque–Bera is a test statistic for testing whether the series is normally distributed. The test statistic measures the difference of the skewness and kurtosis of the series with those from the normal distribution. The reported probability is the probability that a Jarque–Bera statistic exceeds (in absolute value) the observed value under the null hypothesis, i.e. a small probability value leads to the rejection of the null hypothesis of a normal distribution.

Table 4.1: Summary statistics for dedicated monthly US fund flows as a % of NAV. These time series are the bond and equity fund flows for institutional and retail investors as defined.

Summary statistics	$ff^b_{i,t}$	$ff^b_{r,t}$	$ff^e_{i,t}$	$ff^e_{r,t}$
Mean	0.9471	0.0849	0.7993	–0.4729
Median	0.9143	0.0915	0.4815	–0.3776
Maximum	3.7311	2.1625	4.4377	0.6600
Minimum	–3.0091	–2.218	–2.2743	–1.6165
Std. dev.	0.9485	0.9724	1.2368	0.4209
Skewness	–0.6479	–0.2056	0.4810	–0.7442
Kurtosis	6.4057	2.5694	3.3646	3.7548
Jarque–Bera	39.8331	1.0633	3.1755	8.3556
Probability	0	0.5876	0.2044	0.0153

Within the same asset classes, Table 4.2 indicates that the $ff^e_{i,t}$ and $ff^e_{r,t}$ are negatively correlated over the entire period. Hence there are divergences between institutional and retail investor equity fund flow behaviour. With respect to bonds, the investor groups are highly correlated. This may imply that investors are subject to similar sentiment when allocating capital to bonds, however equity fund flow may be based on differences in behaviour. Retail investors are considered to be 'noise traders', as defined in (De Long et al. 1990), and in particular, subject to under- and over-reaction. There may be a difference in trading activity based on momentum or contrarian

Table 4.2: Correlations for dedicated monthly US fund flows as a % of NAV. Included are the macro variables of the LEI and PMI, and consumer confidence CC.

Correlation	$ff^b_{i,t}$	$ff^b_{r,t}$	$ff^e_{i,t}$	$ff^e_{r,t}$	LEI	PMI	CC
$ff^b_{i,t}$	1						
$ff^b_{r,t}$	0.6270	1					
$ff^e_{i,t}$	–0.1704	–0.3975	1				
$ff^e_{r,t}$	0.1279	0.3562	–0.2667	1			
LEI	–0.4644	–0.1915	0.0589	–0.1912	1		
PMI	0.1460	–0.1757	0.1172	0.0461	–0.3540	1	
CC	–0.2797	–0.4223	0.1076	0.3153	0.1693	0.3719	1

views. $ff^e_{i,t}$ is negatively correlated to $ff^b_{r,t}$ and $ff^e_{r,t}$; $ff^e_{r,t}$ is positively related to $ff^b_{i,t}$. Thus $ff^e_{i,t}$ appears to be the single flow variable that is negatively related to all other flows. Further scrutiny is possible using weekly flow and performance data.

CC is negatively correlated to both $ff^b_{i,t}$ and $ff^b_{r,t}$ which implies that bond flows tend to decline when confidence increases and vice versa. The reverse relationship holds for $ff^e_{i,t}$ and $ff^e_{r,t}$; both groups of investors increase equity fund flows when confidence increases. The correlation is noticeably stronger for retail investors. Neither macro benchmark indices, LEI nor PMI, displayed the same conviction. CC has previously been shown to be Granger-caused by past positive equity performance and has also been shown to be a contrarian sentiment indicator for the aggregate stock market. At first blush, in the period under consideration, investor sentiment is seemingly attuned to CC. To explore the relationship further, weekly II data are used. Thereafter, the question pertaining to portfolio insurance will be addressed.

Autocorrelation in retail and institutional time series of dedicated US equity and bond fund flows is next examined to determine whether flows are persistent. A correlogram for the time series estimates Ljung–Box Q-statistics and their p-values for the autocorrelation and partial autocorrelation coefficients. The Q-statistic at lag k is a test statistic for the null hypothesis that there is no autocorrelation up to order k. The institutional investor time series data is autoregressive of order one, with AR(1) coefficient 0.22 (Q-statistic and p-value of 3.63 and 0.06 respectively). Retail equity fund flow monthly data over the entire period appears to be autoregressive of up to two lags with an AR(1) coefficient of 0.47 (Q-statistic and p-value of 16.2 and 0.00), and AR(2) coefficient of 0.24 (Q-statistic and p-value of 20.48 and 0.00). Monthly bond flows were highly autoregressive of up to six and eight lags in the case of institutional and retail investors respectively. Graphically, it is much clearer to comprehend the movement of flows and fund

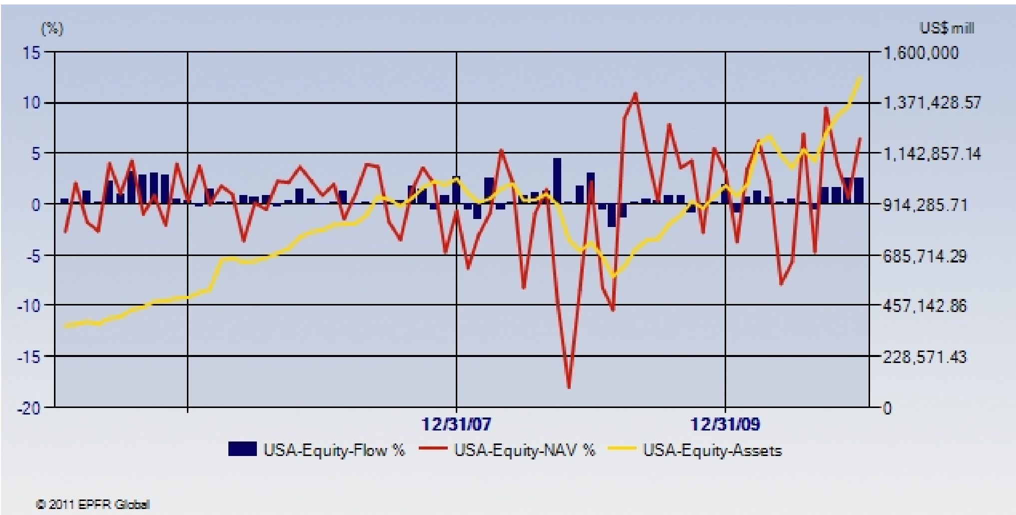

Figure 4.1: Monthly FFs of dedicated US equity funds expressed as % of NAV for institutional investors, % change NAV and total assets over the period.

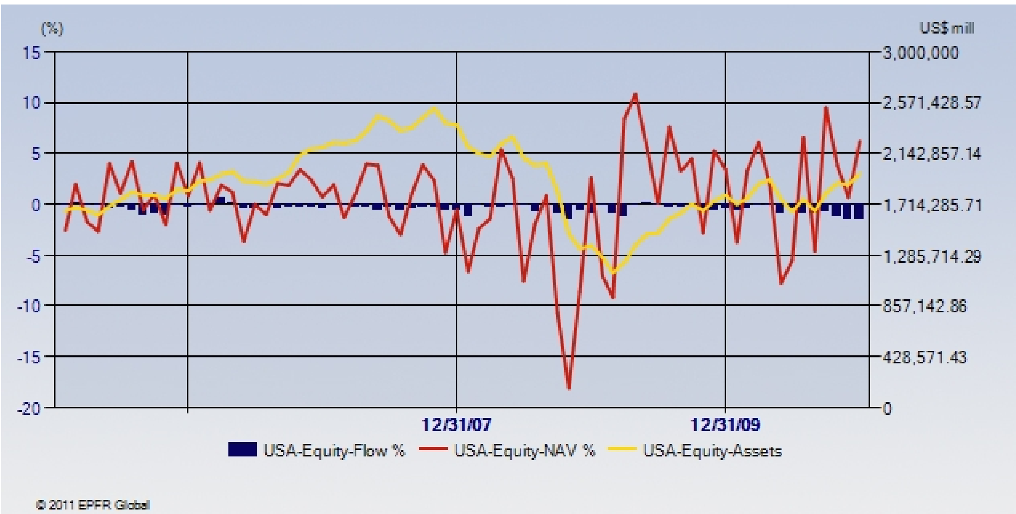

Figure 4.2: Monthly FFs of dedicated US equity funds expressed as % of NAV for retail investors, % change NAV and total assets over the period.

performance. Clearly, US bond flows increased substantially in 2008 for both retail and institutional investors, as defined according the EPFR Global. It appears that the percentage change in NAV and flows are positively correlated for the entire duration for institutional investors. This relationship is mirrored for retail investors from approximately 2008; prior to this date, the flows and performance seem to be negatively related.

The following section addresses time series properties as well as the relationship to respective fund performance and aggregate market performance. Summary statistics, correlations and Granger

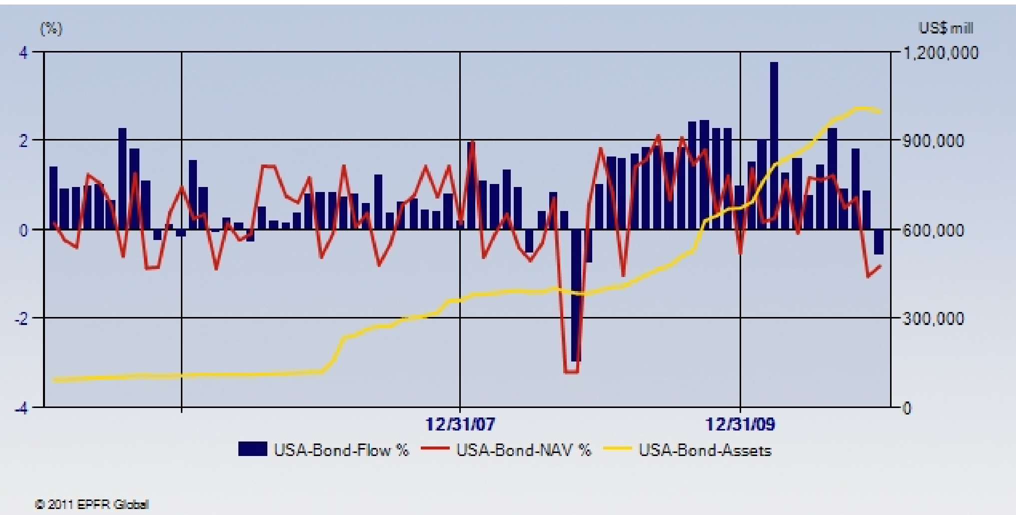

Figure 4.3: Monthly FFs of dedicated US bond funds expressed as % of NAV for institutional investors, % change NAV and total assets over the period.

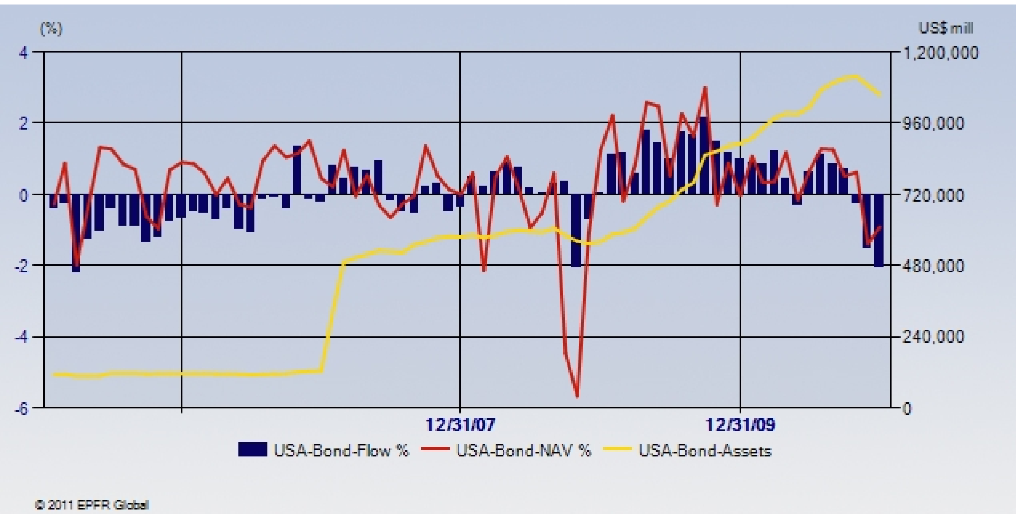

Figure 4.4: Monthly FFs of dedicated US bond funds expressed as % of NAV for retail investors, % change NAV and total assets over the period.

causality for all variables are examined.

4.3.4 Weekly Flows

Weekly data are extracted from the FF dataset between January 2005 and December 2010 for dedicated (100% allocation) US equity and bond funds of combined US and non-US domiciled institutional and retail investors. As discussed in Fratzscher (2011), the time period from January

2005 to December 2010 will be split into pre-crisis and post-crisis regimes in some instances. The pre-crisis period extends from January 2005 to the end of July 2007 and the post-crisis period is then the remainder which includes the crisis, the commencement and termination of which is inexact. Dividing the period is also a means to establish whether certain relationships are robust across all such periods. The entire sample period is from 1/07/2005 to 12/31/2010 (314 observations), the pre-crisis sample is from 1/07/2005 to 7/27/2007 (134 observations) and the post-crisis sample is from 7/27/2007 to 12/31/2010 (180 observations). The number of observations for regressions differ depending on whether lagged dependent variables are included on the right hand side. Time series models are estimated using traditional Box–Jenkins ARMA models in Eviews.

Flow and Returns

Given that there is much debate regarding the relationship between flows and aggregate market returns, it is necessary to determine the relationships that are present within these specific funds. Funds may attract flows due to superior performance and associated sentiment; depending on the nature of the fund in question, investors may require a relatively safe investment, thereby shifting the appeal to specialised bond funds.

Summary statistics over the entire period are provided in Table 4.3. The weekly and monthly statistics are dissimilar for corresponding time series, regardless of the difference in reporting frequency. This tends to arise due to some weeks being split at the end of one month and the start of the next. Thus the data is fairly reliant on reporting periods; caution should be applied when examining across reporting frequencies. Clearly retail equity and bond flows are both negative on average whilst institutional equity and bond flows are in agreement with mean monthly flows, and are positive. Performance of all funds is positive and greater than R_t. The standard deviation of $ff^e_{i,t}$ was the largest within the sample of flows, followed by $ff^b_{i,t}$. Interestingly, $ff^e_{r,t}$ had the lowest sample standard deviation.

Correlations are displayed in Table 4.4. Considering flow relationships, a similar yet clearer account of monthly data can be seen. With regard to bonds, $ff^b_{i,t}$ is positively related to all flows with the exception of $ff^e_{i,t}$: there is a slight positive relationship which then reverts to being negative in the post-crisis period. This might imply capital reallocation between asset classes

Table 4.3: Summary statistics of weekly fund flow, respective fund performance and aggregate market return (in percent) over the period.

Summary statistics	$ff^b_{i,t}$	$_Nff^b_{i,t}$	$ff^b_{r,t}$	$_Nff^b_{r,t}$	$ff^e_{i,t}$	$_Nff^e_{i,t}$	$ff^e_{r,t}$	$_Nff^e_{r,t}$	R_t
Mean	0.18	0.08	–0.04	0.06	0.14	0.09	–0.09	0.10	0.04
Median	0.22	0.11	–0.02	0.12	0.12	0.33	–0.07	0.36	0.22
Maximum	3.26	1.48	3.11	3.33	4.37	10.52	0.50	9.65	11.41
Minimum	–3.20	–2.58	–3.41	–4.93	–2.58	–16.06	–0.87	–15.67	–20.02
Std. dev.	0.60	0.52	0.40	0.67	0.92	2.68	0.16	2.60	2.86
Skewness	0.13	–0.91	–0.74	–1.38	0.78	–0.90	–1.40	–0.98	–1.03
Kurtosis	11.25	5.91	31.08	15.00	6.17	8.60	9.34	8.46	11.96
Jarque–Bera	888.78	153.62	10310.30	1978.26	162.85	451.41	625.74	438.74	1101.59
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

contingent upon risk aversion or fund performance. $ff^b_{r,t}$ follows suit given the slightly stronger negative correlation with $ff^e_{i,t}$ in the post-crisis period. Hence retail investors allocate capital to both asset classes in tandem. With respect to equity, $ff^e_{i,t}$ appears to be negatively related, in varying degrees, to all other flows with the exception of $ff^b_{i,t}$ in the pre-crisis period. It follows that $ff^e_{r,t}$ is slightly negatively correlated to $ff^e_{i,t}$ over all periods and is positively correlated to all flows (over all periods) which is in agreement with monthly data. Thus, institutional equity flow data appear to be negatively related to retail flows, and display alternating yet equivalent mild correlation to institutional bond flows. The negative correlation arises in the latter half of the sample.

Regarding fund flows and respective fund performance, $ff^b_{i,t}$ and $_Nff^b_{i,t}$ are consistently positively correlated over all periods. $ff^b_{r,t}$ is negatively correlated with the fund performance in the pre-crisis period; this then reverts to significant positive correlation in the post-crisis period. $ff^e_{i,t}$ displays zero correlation to respective fund performance which is then followed by positive correlation in the post-crisis period. There is an insignificant negative, then positive, correlation between $ff^e_{i,t}$ to R_t over respective periods. $ff^e_{r,t}$ are positively correlated to its performance and slightly negatively related to R_t over all periods. Institutional and retail bond fund performance are highly correlated. The equity fund performance of both groups is perfectly correlated, and highly correlated to R_t. It appears that the time series $ff^e_{i,t}$ and $ff^e_{r,t}$ react to performance in differing manners, considering that fund performance is perfectly attuned. Hence each group may be subject to different behavioural biases considering that both groups attain essentially the same fund performance. The relationship between retail bond flows and associated performance further supports this notion. Thus it is the institutional equity fund flow–performance as well as the retail bond fund flow–performance correlation which tend to alter in the post-crisis periods. Finally, fund performance across asset classes and investor groups are all positively correlated over all periods.

It is also conceivable that each group of investors might alter fund flow based on performance of the alternative asset class. Examining such correlations, $ff^e_{i,t}$ does not display any significant correlation (mildly negative in the post-crisis period) to ${}_Nff^b_{i,t}$. $ff^b_{i,t}$ is fairly positively related to both ${}_Nff^e_{i,t}$ and R_t in the post-crisis period. The former may be a result of positive correlation between ${}_Nff^e_{i,t}$ and ${}_Nff^b_{i,t}$. $ff^b_{r,t}$ displays positive correlation to ${}_Nff^e_{r,t}$ and slightly less so to R_t in the post-crisis period; this is also evident and significant between $ff^e_{r,t}$ and, ${}_Nff^b_{r,t}$ and R_t. The cross-asset correlations which pertain to each investor group provide further clarification with regard to the flow–performance relationships in sub-periods. Specifically, it seems that institutional investor equity fund flows are not concurrently driven by respective fund performance in the pre-crisis period, however this alters in the post-crisis period. These fund flows also display a slight negative correlation to all other flows during the latter period. Bond flows seem to be concurrently positively related to performance for both groups of investors in the post-crisis period. To establish lead or lagged flow–performance relationships, Granger causality is next examined.

In order to ascertain the direction of information flow, Granger causality (using two lags) over the entire period between all pairs of series (flows as well as percent change in NAV) are examined. The results which reject the null hypothesis of no causality are displayed in Table 4.5. Certain causality relationships may require further clarification. $ff^b_{r,t}$ appears to Granger-cause $ff^b_{i,t}$ which might be a behavioural response to bond fund performance. Noting that ${}_Nff^b_{r,t}$ Granger-causes $ff^b_{i,t}$ and ${}_Nff^b_{i,t}$ Granger-causes $ff^b_{r,t}$, the flow behaviour is credible. Of note is that institutional equity flow is exclusively Granger-caused by its respective fund performance; R_t has no causality implications thereto. Retail investors responded to aggregate market performance R_t as well as performance of all funds.

Continuing with time series properties, a correlogram to establish autocorrelation is examined for the level of each flow variable. $ff^e_{i,t}$ displays no autocorrelation (in agreement with the monthly data) however $ff^e_{r,t}$ results in a positive first-order coefficient AR(1) of 0.30 (Q-statistic 29.2, p-value of 0.00) and second coefficient AR(2) of 0.14 (Q-statistic 35.5, p-value 0.00). Weekly

Table 4.4: Correlations of weekly flow variables and performance for all three periods: pre-crisis (January 2005 to July 2007), post-crisis (August 2007 to December 2010) and the entire period. Included here is the aggregate market return R_t.

Correlation	$ff^b_{i,t}$	${}_Nff^b_{i,t}$	$ff^b_{r,t}$	${}_Nff^b_{r,t}$	$ff^e_{i,t}$	${}_Nff^e_{i,t}$	$ff^e_{r,t}$	${}_Nff^e_{i,t}$	R_t
$ff^b_{i,t}$	1								
${}_Nff^b_{i,t}$ pre-crisis	0.15	1							
post-crisis	0.29								
2005–2010	0.17								
$ff^b_{r,t}$	0.37	0.17	1						
	0.65	0.28							
	0.44	0.17							
${}_Nff^b_{r,t}$	0.06	0.83	–0.15	1					
	0.40	0.81	0.41						
	0.17	0.82	0.08						
$ff^e_{i,t}$	0.08	0.05	0.00	0.01	1				
	–0.08	–0.07	–0.15	–0.18					
	0.01	–0.04	–0.05	–0.13					
${}_Nff^e_{i,t}$	–0.02	0.36	0.07	0.41	0.00	1			
	0.26	0.20	0.20	0.15	0.15				
	0.10	0.23	0.08	0.19	0.11				
$ff^e_{r,t}$	0.04	–0.01	0.06	–0.04	–0.05	0.06	1		
	0.37	0.40	0.32	0.50	–0.10	0.22			
	0.13	0.29	0.09	0.36	–0.08	0.19			
${}_Nff^e_{r,t}$	-0.03	0.36	0.07	0.41	–0.03	0.99	0.05	1	
	0.27	0.21	0.20	0.17	0.14	1.00	0.23		
	0.10	0.23	0.09	0.21	0.10	1.00	0.20		
R_t	0.02	0.08	–0.02	0.15	–0.02	0.53	–0.08	0.52	1
	0.21	0.01	0.14	0.02	0.04	0.60	–0.01	0.60	
	0.09	0.03	0.03	0.04	0.02	0.59	–0.01	0.59	

equity fund flows are displayed in Figure 4.5. It is clear that institutional flows are far more volatile than those of retail investors, particularly between 2007 and 2009, as indicated by the standard deviation over the entire sample period.

Bond fund flows display higher autocorrelation in general with the correlogram of $ff^b_{i,t}$ indicating a third-order autoregressive process. The AR(1) coefficient is 0.15 (Q-statistic of 7.14, p-value 0.01), AR(2) coefficient is 0.17 (Q-statistic of 16.10, p-value of 0.00) and AR(3) coefficient is 0.19 (Q-statistic of 28.70, p-value of 0.00). The institutional bond flow behaviour is characterised by extremely volatile flows in the first half of the series as shown in Figure 4.6 along with $ff^b_{r,t}$. This may be attributed to specific funds being monitored, as some data points pertain to trades of a few large funds, clearly visible in the $ff^b_{r,t}$ series. $ff^b_{r,t}$ is highly persistent as autocorrelation

Table 4.5: Granger causality using two lags for fund flow variables and fund performance over the period. Dependent variables considered pertain to all possible combinations, the null hypothesis being tested. A low p-value implies the null hypothesis is rejected.

Null hypothesis	F-statistic	Prob.
$_Nff^b_{i,t}$ does not Granger cause $ff^b_{i,t}$	5.3146	0.0054
$ff^b_{i,t}$ does not Granger cause $_Nff^b_{i,t}$	2.3224	0.0998
$ff^b_{r,t}$ does not Granger cause $ff^b_{i,t}$	6.4517	0.0018
$_Nff^b_{r,t}$ does not Granger cause $ff^b_{i,t}$	4.9924	0.0074
$ff^b_{i,t}$ does not Granger cause $_Nff^b_{r,t}$	3.0032	0.0511
$ff^e_{i,t}$ does not Granger cause $ff^b_{i,t}$	3.5113	0.0311
$_Nff^e_{i,t}$ does not Granger cause $ff^b_{i,t}$	4.8765	0.0082
$_Nff^e_{r,t}$ does not Granger cause $ff^b_{i,t}$	5.3114	0.0054
$_Nff^b_{i,t}$ does not Granger cause $ff^b_{r,t}$	8.2781	0.0003
$_Nff^b_{i,t}$ does not Granger cause $ff^e_{r,t}$	4.5428	0.011
$_Nff^b_{r,t}$ does not Granger cause $ff^b_{r,t}$	11.7823	1.00E-05
$_Nff^b_{r,t}$ does not Granger cause $ff^e_{r,t}$	3.4058	0.0344
$_Nff^e_{i,t}$ does not Granger cause $ff^e_{r,t}$	27.4849	1.00E-11
$_Nff^e_{r,t}$ does not Granger cause $ff^e_{r,t}$	27.9587	7.00E-12
R_t does not Granger cause $ff^b_{r,t}$	3.9032	0.0212
R_t does not Granger cause $ff^e_{r,t}$	54.9588	4E-21

coefficients and partial autocorrelation coefficients extend beyond the 5% confidence intervals for up to 38 lags.

To summarise:

- **Institutional Investors**
  * *Bond Flows – $ff^b_{i,t}$:* These bond fund flows are positively correlated to all flows with the exception of the slight negative relationship to institutional equity fund flows in

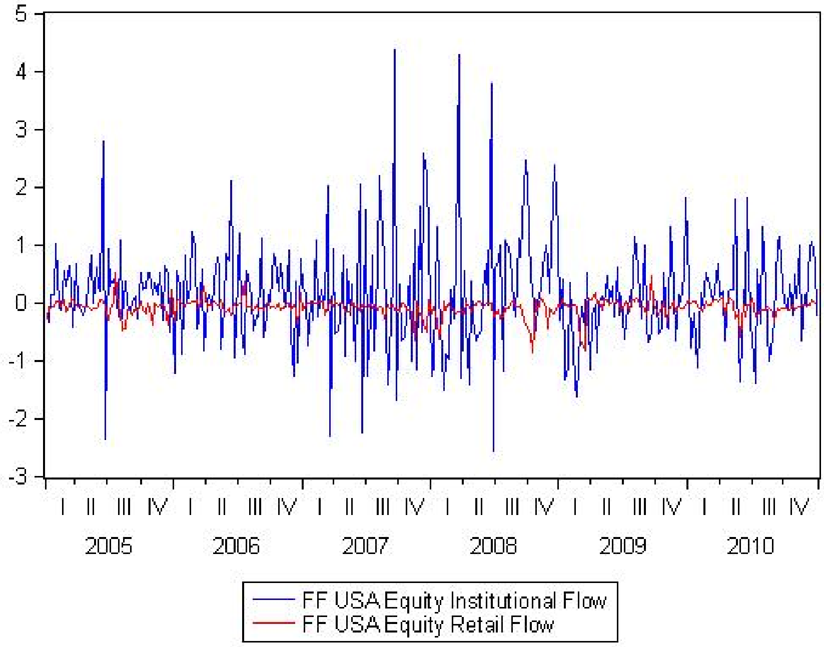

Figure 4.5: Weekly FFs of dedicated US equity funds expressed as % of NAV for retail and institutional investors over the period.

the post-crisis period. Flows are positively contemporaneously related to own fund performance; two-way Granger causality exists. Flows seem to be fairly persistent and appeared to be Granger-caused by performance in general. This flow variable has the highest positive correlation to aggregate market returns in the post-crisis period.

  * *Equity Flows – $ff^e_{i,t}$:* These flows are unique in the sense that there is no causality associated with own fund performance. Past flows do not appear to persist as there is no autocorrelation over the whole sample period. It is only in the pre-crisis period that there is a slight positive correlation to institutional bond fund flows. During the latter half of the sample period, these flows are slightly negatively related to all other flows. There is zero correlation with its own fund performance in the pre-crisis period, followed by a positive concurrent correlation to own fund performance, as well as (very slightly) to aggregate market returns in the post-crisis period.

– **Retail Investors**

  * *Bond Flows – $ff^b_{r,t}$:* These flows are very much in line with institutional bond fund

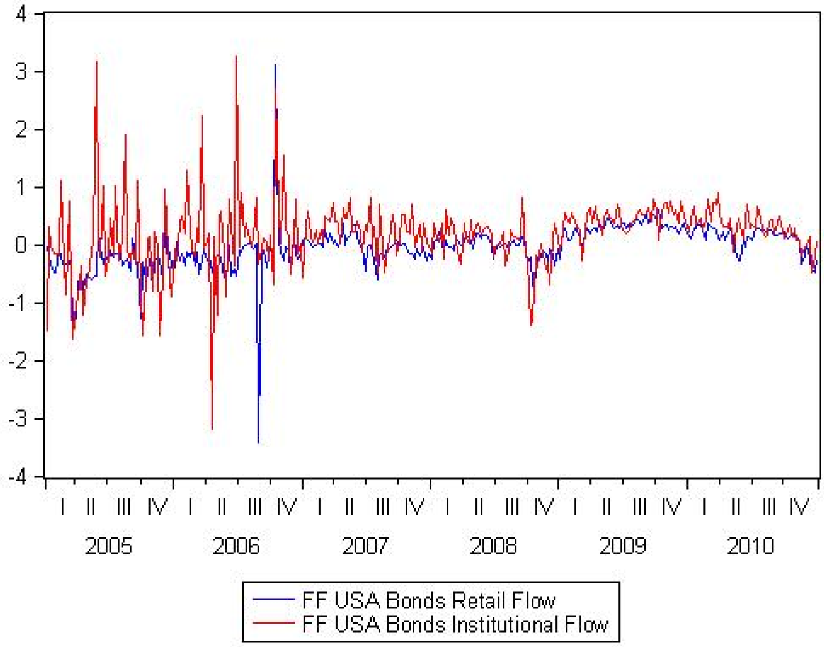

Figure 4.6: Weekly FFs of dedicated US bond funds expressed as % of NAV for retail and institutional investors over the period.

flows. The only difference is that the contemporaneous correlations to own-fund performance is negative in the pre-crisis period; this then reverts to being positive in the post-crisis period. Granger causality is from fund performance to flows and uniquely from aggregate market performance to retail investor flows. Positive correlations exist between these flows and aggregate returns in the post-crisis period. This series is extremely persistent.

* *Equity Flows* – $ff^{e}_{r,t}$: Retail equity funds are positively correlated to both institutional and retail bond flows in the latter period. There is also a slight correlation to institutional equity flows over all periods. These flows are Granger-caused by own fund performance, ${}_{N}ff^{e}_{i,t}$ as well as that of aggregate market returns. These flows are very slightly negatively contemporaneously correlated to R_t over all periods. The series is fairly persistent.

Having explored the relationships between flow, performance and aggregate market performance over each sub-period, in general it appears that performance Granger-causes flows which conforms to the *feedback trader hypothesis*. Flows did not appear to Granger-cause performance with the exception of the two-way causality of institutional bond funds. Uniquely to retail investors, aggregate market performance Granger-causes flows over the entire period. Institutional equity fund flow tends to differ as performance, over the entire period, is unrelated to flow. However, a zero contemporaneous correlation, followed by a slight positive correlation, exists between these fund flows and own-fund performance over the pre- and post-crisis periods. There is no autocorrelation (over the whole period) present, and therefore it appears that institutional equity flows may be determined by factors other than performance. All other flows appear to be consistent with respect to correlations to each other as well as performance measures.

Given that flows are tantamount to sentiment, the following section examines the relationship between fund flows and sentiment measures. The fund flows are an aggregation of US and non-US domiciled fund flows (global sentiment) whereas the II measure is based on the opinions of US newsletter writers. In this section, the VIX and TED spread which are global measures of risk and liquidity will also be examined along with the SPX option-implied skew and AAII. The latter is included due to the close relationship that has been shown to exist between these indices. Henceforth, retail flows will be excluded from the analysis as the principal hypothesis pertains to institutional sentiment.

Investor Sentiment

This section begins with a detailed comparison between the US survey-based sentiment measures and the common global risk factors, in addition to the option-implied skew; these are all deemed sentiment-related variables. Data consist of the AAII and II bull–bear spread, the VIX, the TED spread, and the index option-implied skew η_t^3.

II and AAII surveys are released on Tuesdays, the VIX and TED spread are recorded on the Friday of the week and η_t^3 is averaged over the week, calculated on the Friday of each week. All units are expressed as a percentage, with the exception of the skew η_t^3 and the TED spread which is expressed in basis points (1 bp$=$ 1% of 1%). As in the previous section, summary statistics, correlations and Granger causality are displayed for sentiment-related variables. This is followed by time series analysis of II. In particular, II is regressed on the VIX, TED spread, η_t^3 and the AAII.

The summary statistics are reported in Table 4.6 over the period 7 January 2005 to 31 December

2010 on a weekly basis, followed by correlations in Table 4.7. Results indicate that the VIX and TED spread are negatively correlated to II and AAII over all periods, as expected. Since the VIX increases after the aggregate market declines, investors are likely to become less optimistic. II is positively correlated to AAII (retail investor sentiment), regardless of the difference in fund flow behaviour of these groups. The skew is also positively related to II and AAII, thereby indicating a less negative skew (this is clearly on average negative for SPX options), is concurrently related to more bullish than bearish investor opinions. [28] As the TED spread widens and liquidity decreases, a more negatively skewed returns distribution is observed. Results are robust across periods.

Table 4.6: Summary statistics of weekly sentiment variables which include survey-based as well as option-implied measures over the period.

Summary statistics	AAII	II	η_t^3	VIX	TED
Mean	1.43	16.77	–0.13	21.64	65.44
Median	1.93	19.60	–0.12	18.61	38.97
Maximum	46.87	42.40	0.14	79.13	463.61
Minimum	–51.35	–32.20	–0.41	10.02	11.06
Std. dev.	17.51	16.13	0.09	11.78	63.43
Skewness	–0.16	–0.79	–0.13	2.00	2.44
Kurtosis	2.72	3.02	2.98	7.94	11.23
Jarque–Bera	2.35	32.75	0.85	526.64	1193.21
Probability	0.31	0.00	0.65	0.00	0.00

Table 4.7: Correlations of weekly sentiment variables, as in Table (4.6), for all three periods: pre-crisis (January 2005 to July 2007), post-crisis (August 2007 to December 2010) and the entire period.

Correlation	AAII	II	η_t^3	VIX	TED
AAII	1				
II (pre-crisis)	0.42	1			
post-crisis	0.57				
2005–2010	0.56				
η_t^3	0.19	0.22	1		
	0.25	0.30			
	0.30	0.39			
VIX	–0.48	–0.41	–0.49	1	
	–0.35	–0.67	–0.23		
	–0.41	–0.70	–0.39		
TED	–0.18	–0.04	–0.30	0.28	1
	–0.37	–0.57	–0.42	0.59	
	–0.37	–0.59	–0.45	0.66	

[28]The skew here has been measured on the Friday of the week, hence it appears that there is a lag of three days. Checking the skew averaged over the week from Wednesday to Tuesday does not alter the results.

Granger causality is also examined as this establishes information flow pertaining to known relationships. This too serves to illustrate established results of previous research. Table 4.8 reports only those results which lead to a rejection of the null hypothesis. It appears that the VIX, TED spread and the skew precede information from survey results for both II and AAII. The VIX and TED spread are particularly responsible as causality runs from both these series to the skew. However, the VIX and the skew when both linearly interpolated to reflect a 30-day measure, are contemporaneously correlated given they are derived from the same options data, as in Chapter 3. The difference here may arise due to the maturity of options. The skew pertains to the nearest maturity, since macro news is most likely to affect these options. There are two two-way causality relationships between the skew and both survey measures. This instils further confidence in the use of the skew as an institutional sentiment measure. Figure 4.7 displays the VIX and the TED spread. The series are highly correlated as indicated in Table 4.7.

Table 4.8: Granger causality for sentiment-related variables over the entire period. Results which indicate a rejection of the null hypothesis are shown, reflected in the low p-value.

Null hypothesis	F-statistic	Prob.
TED does not Granger cause VIX	12.2884	7.00E-06
TED does not Granger cause II	4.1446	0.0167
TED does not Granger cause η_t^3	12.2268	8.00E-06
VIX does not Granger cause II	6.4170	0.0019
VIX does not Granger cause AAII	18.5030	3.00E-08
VIX does not Granger cause η_t^3	5.6313	0.0040
II does not Granger cause AAII	22.4507	8.00E-10
η_t^3 does not Granger cause II	3.4324	0.0336
II does not Granger cause η_t^3	3.9452	0.0203
η_t^3 does not Granger cause AAII	12.4464	6.00E-06
AAII does not Granger cause η_t^3	2.7673	0.0644

Individual relationships are examined by regressing II on the following: the VIX, TED spread, η_t^3 and the AAII. The first three variables are recorded on the Friday of week t whereas II and AAII are from week $t+1$ to avoid look-ahead bias. Over the period 2005–2010, weekly II data fit an AR(1) model with lagged coefficient 0.93 (t-stat 38.14, p-value 0.00, adjusted R-squared is

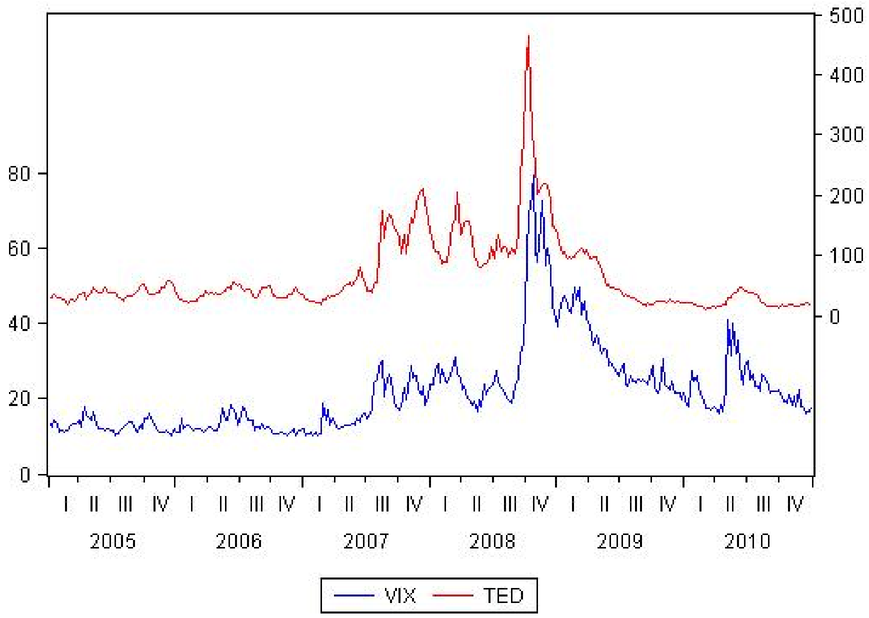

Figure 4.7: The CBOE VIX (left axis) in percent, and TED spread (right axis) measured in basis points over the period.

0.90) and constant term 1.25 (t-stat 2.32, p-value 0.02). The residuals fit an AR(1). The AIC is minimised when selecting the best fit. A lag of one is included in all regressions. All equations are fit using appropriate AR and MA terms for errors. In an AR(p) model, the autocorrelations decay to zero for long lags, while the $p+1$ partial autocorrelation (and beyond) goes abruptly to zero. The reverse is true for an MA model. EViews estimates AR models using nonlinear regression techniques with HAC standard errors and covariance (Bartlett kernel, Newey–West fixed bandwidth = 6.0000). Regression statistics for the entire period under consideration are reported.

The OLS regression of the survey-based institutional variable II_t to be estimated is as follows:

$$II_t \quad = \quad \alpha + \beta_1 II_{t-1} + \beta_2 x_{t-1}, + \epsilon_t \tag{4.1}$$

where x_{t-1} is the exogenous time series and ϵ_t are the residuals which are fitted according to an ARMA model to ensure that no autocorrelation or heteroscedasticity is present. In the case of AAII, the data are available at the same weekday as II thus x_t will be used. Results are displayed in Table 4.9. Each column represents the coefficients to the variables which are in the regressions equation. This format will be retained throughout. All variables are statistically significant however the adjusted R^2 does not improve when exogenous variables are added. The results serve to confirm that if the VIX increases by 1%, the II variable decreases by 0.33%. A 1 basis point increase in the TED spread results in a decrease in the II of 0.02%. If the skew increases by 0.01 units, the II will then increase by 0.06%.

Table 4.9: Regressions of weekly II data over the entire period 2005–2010, as given by equation (4.1). The t-statistic and p-value are reported below each coefficient as indicated adjacent to α.

II_t	Variable (2005–2010)					
Value	α	1.25	1.78	16.31	4.31	2.51
t-stat.		2.33	4.37	5.27	2.76	3.13
p-value		0.02	0.00	0.00	0.01	0.00
	II_{t-1}	0.93	0.88	0.46	0.83	0.91
		38.14	46.23	4.64	14.00	35.98
		0.00	0.00	0.00	0.00	0.00
	$AAII_t$		0.12			
			7.12			
			0.00			
	VIX_{t-1}			–0.33		
				–4.31		
				0.00		
	TED_{t-1}				–0.02	
					–2.24	
					0.03	
	η^3_{t-1}					7.57
						2.07
						0.04
Adjusted R^2		0.90	0.91	0.91	0.90	0.90

Flow and II Sentiment

Dedicated institutional US bond and equity fund flow and performance data are examined in relation to the US survey-based measure of II. This serves to gauge whether the fund flows (global sentiment), performance and this measure of US institutional investor sentiment are consistent. Fund-related data are measured from Thursday to Wednesday and reported on the Thursday of the week. Given that Indro (2004) established a positive and statistically significant relationship between lagged fund flows and II bullish sentiment, caution is to be applied when comparing results as there are stark differences from the outset: the funds flow data (ICI) tracks only those funds that are registered in the US. This omits a large universe of US equity and US bond funds which are domiciled in Europe or Asia, but invest in the US market. The use of all domiciled funds aggregates the opinions of investors globally, regarding the state of the US, as well as non-US economies. It is also the case that the data capture different groups of investors. The variable used in this research is the II bull–bear spread as opposed to the percentage of bullish opinions.

Granger causality for institutional fund flows, performance and II are in Table 4.10; only those results which lead to a rejection of the null hypothesis are displayed. Clearly, institutional fund performance Granger-causes II. II Granger-causes bond fund flows. Performance of both asset classes tends to Granger-cause II. Examining regressions more closely with II as a dependent variable and either flows or performance as independent variables, no further relationships were perceived. In particular, II did not display any statistical significance when flows were regressed on II or lagged II.

Table 4.10: Granger causality for the bull–bear spread II, institutional fund flows and fund performance.

Null hypothesis	F-statistic	Prob.
II does not Granger cause $ff^b_{i,t}$	3.1038	0.0463
$_Nff^b_{i,t}$ does not Granger cause II	3.3667	0.0358
$_Nff^e_{i,t}$ does not Granger cause II	7.2165	0.0009

Hence II is a momentum variable and appears to be Granger-caused by other sentiment-related variables. II is not significantly related to institutional sentiment, as measured by fund flows. II is however Granger-caused by the VIX, TED spread and the skew, the former two variables being highly correlated. The following section examines the option-implied skew and relationship to institutional fund flows.

Flow and Portfolio Insurance

Henceforth, the skew is the primary sentiment-related variable to be examined. It is related to the VIX by construction, the TED spread, and daily data suggests it is positively correlated to movements in the underlying (Chapter 3). The slope of the implied volatility smile of index options for a given maturity is an indication of institutional investors' requirements for insurance; the steeper the smile, the greater the demand for such insurance. This manifests in the option-implied skew. Therefore, it is necessary to establish whether global institutional sentiment, as measured by dedicated US institutional fund flows, is aligned with the option-implied skew of the aggregate market index. Fund flows have been shown to be preceded by returns given that performance Granger-causes flow, as in Table 4.5, with the exception of institutional equity flow. Regressing η_t^3 on institutional fund-related variables a means to establish whether flow variables are consistent with views regarding possible downwards market movements in the immediate future.

Data to be examined in this section are the skew η_t^3, the VIX, the TED spread, $ff_{i,t}^b$, $_Nff_{i,t}^b$, $ff_{i,t}^e$, $_Nff_{i,t}^e$ and the aggregate market weekly percentage performance R_t. Table 4.8 indicates that the VIX, TED spread and the skew precede information from survey results for both II and AAII. It is also the case that II Granger-causes $ff_{i,t}^b$. From these simple relationships, information flow and Granger causality can be expected in the case of the VIX, TED spread, the skew and flow. Reporting statistically significant Granger causality in Table 4.11, it is evident that institutional bond flows Granger-cause skew. This provides initial insight into the hypothesis pertaining to equity portfolio insurance and bond fund flows. Additionally, equity fund performance Granger-causes skew which is then relevant for the second hypothesis regarding performance and insurance. It is also the case that both skew and TED spread Granger-cause institutional equity flow – this will be further discussed. In the instance of fund performance Granger-causing the VIX or TED spread, the complexity of the relationships between financial markets may give rise to feedback, and thereby create an appearance of precedence when in fact, the variables are reflecting coincidental information.

In light of this information, it is clear that index option markets are a useful vein wherein sentiment of institutional investors manifests. Thus far, the skew has been shown to be related to both II and AAII as well as the global factors (VIX, TED spread). The risk-neutral distribution embodies forward-looking sentiment pertaining to the underlying index at the relevant maturity. These simple causality relationships indicate that the skew is a manifestation of both aggregate market momentum as well as the markets perception of near-term equity market performance. The skew also Granger-causes $ff_{i,t}^e$, and hence may be useful as an indicator to forecast equity fund flows. The stock market is highly integrated with, and reacts to, the real economy; options markets have also been shown to react to fundamental macro news. The skew is then that single measure which appears to be all-encompassing.

Proceeding, the time series properties of the skew are established over the weekly period January 2005 to July 2007, followed by August 2007 to December 2010. To ensure that η_t^3 is not a unit

Table 4.11: Granger causality for the VIX, TED spread, skew, fund flows and performance.

Null hypothesis	F-statistic	Prob.
$ff^b_{i,t}$ does not Granger cause η^3_t	4.4195	0.0128
η^3_t does not Granger cause $ff^e_{i,t}$	6.8208	0.0013
$_N ff^e_{i,t}$ does not Granger cause η^3_t	4.8119	0.0088
$_N ff^b_{i,t}$ does not Granger cause VIX	2.6121	0.075
TED does not Granger cause $ff^b_{i,t}$	6.9550	0.0011
TED does not Granger cause $ff^e_{i,t}$	4.7556	0.0092
TED_t does not Granger cause R_t	8.9868	0.0002
$_N ff^e_{i,t}$ does not Granger cause TED	4.7956	0.0089

root process over the entire period, an ADF test including a constant is performed. The t-statistic of –4.38 (p-value of 0.00) is smaller than the critical values at the 1% (–3.45), 5% (–2.87) and 10% (–2.57) levels which leads to a rejection of the null hypothesis of the presence of a unit root. The best fit is an ARMA(1,1) which is also consistent over individual periods. The errors displayed neither heteroscedasticity, nor autocorrelation.[29] Results are provided in Table 4.12. AR and MA Roots are the inverted roots of the equation.

- The next set of regressions address Hypothesis 1: *Increases in institutional dedicated US bond flows signal a decrease in the aggregate market skew.*

  The regressions estimated are

$$\eta^3_t = \alpha + \sum_{i=1}^{k} \beta_i \eta^3_{t-i} + \sum_{j=1}^{p} \varphi_j x_{j,*} + \theta\epsilon_{t-1} + \epsilon_t, \tag{4.2}$$

  where β_i refers to the AR(i) coefficient, φ_j is the coefficient of the exogenous variable $x_{j,*}$ which may be lagged by one week or current. Thus $x_{j,*} = x_{j,t-1},\ x_{j,t}$ respectively. θ refers to the MA(1) coefficient. In the second period, the model best suited is adjusted by including an AR(4) term and removing the MA(1) term when necessary. Included are the contemporaneous aggregate market return R_t and the TED spread. The VIX contains relatively similar information to the TED spread as expressed in the correlation as well as precedence of information in the Granger causality, and therefore is not included here. Results are in Tables 4.13, 4.14 and 4.15. Regressions are performed using the HAC

[29] If the autocorrelation is within the two standard error bounds computed as $\pm 2/\sqrt{N}$, where N is the sample size, it is not significantly different from zero at (approximately) the 5% significance level.

Table 4.12: Regression results for the weekly option-implied skew η_t^3, averaged over the week on Friday.

Sample	Variable	Coefficient	Std. error	t-statistic	Prob.	AR roots	MA roots
1/14/2005–	α	–0.1027	0.0161	–6.3997	0	0.87	0.69
7/27/2007	AR(1)	0.8726	0.0946	9.2294	0		
	MA(1)	–0.6918	0.1354	–5.1097	0		
	Adj. R-squared	0.1095	AIC		–2.4696		
	F-statistic	9.1182					
	Prob(F-stat.)	0.0002					
7/27/2007–	α	–0.1267	0.0293	–4.3197	0	0.96	0.85
12/31/2010	AR(1)	0.9628	0.0216	44.5866	0		
	MA(1)	–0.8474	0.0519	–16.3407	0		
	Adj. R-squared	0.2933	AIC		-2.2608		
	F-statistic	38.1370					
	Prob(F-stat.)	0					
7/29/2005–	α	–0.1352	0.0223	–6.0653	0	0.95	0.74
12/31/2010	AR(1)	0.9466	0.0281	33.5766	0		
	MA(1)	–0.7433	0.0575	–12.9167	0		
	Adj. R-squared	0.2720	AIC		–2.2764		
	F-statistic	53.8773					
	Prob(F-stat.)	0					

coefficient covariance estimator (Newey–West). Regressing the skew on institutional bond flows over pre-crisis and post-crisis periods, it appears that the relationship is statistically significant for lagged flows $ff_{i,t-1}^b$ in the pre-crisis period and concurrent flows $ff_{i,t}^b$ in the post-crisis period. There are also stark differences pertaining to the signs.

Under standard market conditions (pre-crisis period), positive dedicated US institutional bond fund flows $ff_{i,t}^b$ in a week result in a decease in η_{t+1}^3 in the following week between 2005 and mid-2007. In particular, a 1% increase of $ff_{i,t}^b$ in week t leads to a –0.018 decrease in the skew in week $t+1$ over this period. Upon inclusion of R_t and TED_t, results indicate that positive weekly returns, an increase in liquidity (a decrease in the TED spread) as well as flows out of bond funds, lagged by one week, tend to result in an increase in the skew (less negative). The TED spread is measured in bps, R_t and $ff_{i,t-1}^b$ are percentages and η_t^3 is in units. Positive equity market performance may lead to bond outflows into equity funds as risk aversion decreases and sentiment increases, the latter measured by the index option-implied skewness. Lagged positive bond flows preceded a decrease in the skew. Granger causality runs from both bond and equity fund performance as well as R_t to $ff^b_{i,t}$ over the entire period. In section 4.3.4, it can be seen that $ff^b_{i,t}$ is very slightly positively correlated to $ff^e_{i,t}$ during the initial period; the relationship alters sign during the post-crisis period. However $ff^e_{i,t}$ is not correlated to its own fund performance in this period. $ff^b_{i,t}$ did not display a significant correlation to R_t in the initial sample period either. Similarly, this reverts to a significant positive correlation during the post-crisis period. These flows are significantly positively related to their own fund performance, equity fund performance and R_t in the second period. In the first period, these funds do not display any significant correlation to bond or equity fund performance. Hence during this period, there are no obvious relationships which should lead to this result. Granger causality exists between II, the skew and $ff^b_{i,t}$ over the entire period. Thus during the pre-crisis regime, positive institutional bond flows which are fairly persistent yet uncorrelated to own-fund performance over this period, result in an increase in portfolio insurance in the following week, evidenced by a decrease in the skew. Institutional investor behaviour appears to be consistent, albeit with a lag of one week. This serves to confirm the hypothesis and reinforces the use of fund flows as a global sentiment measure. However, institutional investor behaviour appears to adapt to the heightened risk levels and decreased liquidity in the latter half of the sample.

In the post-crisis period, the relationship has altered to yield a positive and statistically significant coefficient for current bond flows. Hence regardless of near-term equity market perceptions, bond flows adhered to the flight-to-safety hypothesis. From mid-2007 to December 2010, there is a positive contemporaneous relationship between η^3_t and $ff^b_{i,t}$. Bond flows and portfolio insurance appear to move in the same direction over this period. Having explored numerous flow–performance relationships, it is clear that $ff^b_{i,t}$ over the post-crisis period displays positive contemporaneous correlation with all fund performance measures as well as R_t. It is also Granger-caused by performance. One possible clue for the alternation of sign between skew and bond flows is to observe that bond flows and equity flows are slightly negatively correlated over this period. Bond flows and equity performance are however positively related. Equity flows are only slightly positively correlated to own-fund performance over this period. Positive fund performance in general Granger-causes bond flows, however institutional equity flows remain elusive. Positive lagged and contemporaneous equity fund performance may lead to an increase in the skew as there is less of a requirement for portfolio insurance as institutional investors become more bullish as a result of market momentum. This then accounts for the shift in dynamics and forms the empirical analysis to confirm the second hypothesis. It is also the case that during the latter period, the relationship between skew and bond flows alters as a result of market conditions. This is supported by Fratzscher (2011) wherein the author finds the Lehman event to have triggered capital repatriation to the US and some advanced economies after exiting EMEs, which was perceived to be stronger for bond flows than for equity.

Lagged bond flows did not improve as inclusion yielded weak regression results; including R_t then TED_t served to decrease the statistical significance. Thus the relationship that existed prior to August 2007 seems to be relevant for the period in which global risk – the VIX – was relatively low and liquidity was well below the maximum (464 bps). The relationships with R_t and TED_t are of the same inclination as the pre-crisis period, however the econometric significance is decreased.

Over the period 2005–2010, the lagged bond flows tend to dominate, as regression results did not improve upon inclusion of current bond flows. What can be seen is that 1% increase in one-week lagged institutional investor bond flows results in a decrease in the skew of –0.01 over the entire period; this relationship is statistically significant. The results over the separate periods appear contradictory, however the latter half was characterised by flows into all AE funds and particularly US bond funds.

- The next set of regressions addresses Hypothesis 2: *Positive equity fund performance leads to (or is accompanied by) an increase in the skew.*

  Contemporaneous and lagged positive daily aggregate market returns are associated with an increase in the skew, as is shown in Chapter 3 and Bondarenko (2000) where η_t^3 refers to the 30-day implied skew that is linearly interpolated from appropriate option maturities on a given business day. It therefore follows that positive institutional equity fund performance over a period may render institutional investors optimistic, and therefore reduce the requirement for portfolio insurance. The regression results pertaining to Hypothesis 1 indicate that skew is positively contemporaneously related to weekly aggregate market returns. R_t is also positively correlated to ${}_Nff_{i,t}^e$ which therefore implies that a similar relationship between skew and weekly institutional equity fund performance should exist across all sub-

Table 4.13: Regression results for the weekly option-implied skew and institutional bond fund flows from January 2005 to July 2007, as described in equation (4.2).

η_t^3	Variable	(2005 to mid-2007)		
value	α	–0.0993	–0.1011	0
t-stat.		–6.6206	–7.2808	
p-value		0	0	
	AR(1)	0.8545	0.8652	0.7500
		7.5349	8.3012	3.8127
		0	0	0.0002
	MA(1)	–0.6704	–0.7062	–0.5622
		–4.1366	–4.8442	–2.3217
		0.0001	0	0.0218
	$ff_{i,t-1}^b$	–0.0185	–0.0197	–0.0202
		–3.3465	–3.1877	–3.4646
		0.0011	0.0018	0.0007
	R_t		0.0115	0.0104
			2.9367	2.7706
			0.0039	0.0064
	TED_t			–0.0025
				–9.5055
				0
Adjusted R^2		0.1367	0.1891	0.2347

periods. Hence one can expect consistent past positive equity fund performance to lead to an increase in the skew. Institutional equity fund flows display zero correlation, followed by a slight positive correlation to own-fund performance in the pre- and post-crisis periods respectively. This and the lack of persistence deems the use of such flows for exposition purposes futile. Interestingly, the skew and TED spread Granger-cause $ff_{i,t}^e$ over the entire period; thus the skew during week t may be relevant to institutional equity fund flow in week $t+1$ as causality is interpreted as information precedence. The skew is directly related to equity market performance, and therefore the bond fund flow post-crisis results of Hypothesis 1 can be justified as being a crisis phenomenon given the correlations which arise between flows and performance during this period. Thus equity performance possibly trumps that of bond flows in this instance. To prove Hypothesis 2, a momentum variable ${}_N^m ff_{i,t}^e$ is defined as the four-week rolling average of ${}_N ff_{i,t}^e$. η_t^3 will be regressed on the momentum variable, adding in R_t, the VIX and $ff_{i,t-1}^b$ separately. Lagged bond flows are included to establish the strength of the combined relationships. As before, regressions

Table 4.14: Regression results for the weekly option-implied skew and institutional bond fund flows from August 2007 to December 2010, as defined in equation (4.2).

η_t^3	Variable	(mid-2007 to 2010)		
value	α	–0.1353	–0.1618	–0.1374
t-stat.		–4.6973	–8.5380	–7.4322
p-value		0	0	0
	AR(1)	0.9647	0.3607	0.3295
		40.1539	5.1084	4.7884
		0	0	0
	MA(1)	–0.87		
		–17.5026		
		0		
	AR(4)		0.3100	0.2985
			6.8127	5.578
			0.00	0.00
	$ff_{i,t}^b$	0.0392	0.0367	0.0246
		2.0314	2.1072	1.4151
		0.0437	0.0365	0.1588
	R_t		0.003	0.0026
			1.7603	1.4368
			0.0801	0.1526
	TED_t			–0.0003
				–1.7951
				0.0744
Adjusted R^2		0.3045	0.3409	0.3468

estimated are of the form

$$\eta_t^3 \quad = \quad \alpha + \sum_{i=1}^{k} \beta_i \eta_{t-i}^3 + \sum_{j=1}^{p} \varphi_j x_{j,t} + \theta \epsilon_{t-1} + \epsilon_t, \tag{4.3}$$

where $k = 1,\ 2,\ 3$ depend on the fitted equation and $x_{j,t}$ refers to the momentum variable as well as other exogenous variables to be included.

Results are in Tables 4.16, 4.17 and 4.18. The TED spread performed poorly when included with ${}_N^m ff_{i,t}^e$ hence results are omitted. It is also the case that ${}_N^m ff_{i,t}^e$ together with both VIX_t and R_t did not yield any statistically significant results.

The above results in accordance with Granger causality establish that the skew, which is a reflection of institutional investors perceptions of near-term aggregate market performance as well as the demand for insurance, is positively contemporaneously related to the momentum variable ${}_N^m ff_{i,t}^e$. When included in the regressions, $ff_{i,t-1}^b$ clearly has an opposite sign

Table 4.15: Regression results for the weekly option-implied skew and institutional bond fund flows from January 2005 to December 2010.

η_t^3	Variable	(2005–2010)		
value	α	–0.1300	–0.1302	–0.1003
t-stat.		–6.3088	–6.4297	–6.8606
p-value		0	0	0
	AR(1)	0.9400	0.9426	0.8977
		37.6183	38.3657	20.1501
		0	0	0
	MA(1)	–0.7180	–0.7312	–0.7098
		–11.5369	–11.7572	–9.2728
		0	0	0
	$ff_{i,t-1}^b$	–0.0193	–0.0185	–0.0207
		–3.0749	–2.9175	–3.4267
		0.0023	0.0038	0.0007
	R_t		0.0037	0.0030
			1.9404	1.3683
			0.0533	0.1722
	TED_t			–0.0004
				–2.5852
				0.0102
Adjusted R^2		0.3098	0.3228	0.3384

to that of equity momentum, the degree of which varies depending on the market regime. In the pre-crisis period, the equity momentum variable appears to dominate, as a 1% increase in both variables tend to lead to an increase in the skew of 0.02. Over the post-crisis period, including current bond flows performed poorly. Thus the positive contemporaneous relationship between η_t^3 and $ff_{i,t}^b$ in Table 4.14 is imperceptible here. The inclusion of $ff_{i,t-1}^b$ with ${}_N^m ff_{i,t}^e$ yielded statistically significant results over all periods for both variables, however the significance of $ff_{i,t-1}^b$ in the post-crisis period is questionable, as indicated by the t-statistic and p-value. Thus the skew appears to be far more susceptible to momentum in this period than bond flows thereby indicating that portfolio insurance is determined more so by positive equity fund performance, using the four-week rolling average as the period under consideration, than institutional bond flows. Clearly, institutional investors allocated capital to bonds regardless of perceptions pertaining to equity market performance in this period, as was established in Fratzscher (2011). This then implies that sustained positive equity fund performance reduces the requirement for portfolio insurance during all market regimes and is more relevant to determine movements in the skew. Institutional allocation

Table 4.16: Regression results for the weekly option-implied skew and equity fund momentum from January 2005 to July 2007, defined in equation (4.3).

η_t^3	Variable (2005 to mid-2007)				
value	α	–0.1036	–0.1043	0.1153	–0.1030
t-stat.		–10.8818	–11.0766	2.9610	–12.7887
p-value		0	0	0.0037	0
	AR(1)	0.2260	–0.3547	–0.4727	–0.4144
		2.9156	–1.9234	–2.137	–1.8139
		0.0042	0.0567	0.0345	0.0721
	MA(1)		0.5677	0.6223	0.5449
			3.5451	3.1715	2.5968
			0.0006	0.0019	0.0105
	${}^{m}_{N}ff^{e}_{i,t}$	0.0285	0.02678	0.0019	0.0400
		2.1979	1.9869	0.1466	3.5701
		0.0298	0.0491	0.8837	0.0005
	R_t		0.0103		
			2.8769		
			0.0047		
	VIX_t			–0.0164	
				–5.8238	
				0	
	$ff^{b}_{i,t-1}$				–0.0247
					–4.1257
					0.0001
Adjusted R^2		0.1081	0.1457	0.2579	0.1666

to bond funds and the subsequent requirement for portfolio insurance tends to occur during 'normal' market regimes whereby liquidity is relatively high (regressions in Hypothesis 1) and volatility is well within the average plus two standard deviation band (65%). Including the weekly aggregate market return R_t yielded a positive coefficient, however the statistical significance varied over periods, the post-crisis being unremarkable. Thus, weekly market returns might not carry enough momentum to create demand for portfolio insurance. The daily results in Chapter 3 may not apply here, as the measurement of η_t^3 here is averaged over the week and R_t is the weekly return. As expected, the VIX is highly related to the skew: as global fear increases, so too does the requirement for portfolio insurance. Methods of construction naturally result in differences as the VIX is a 30-day implied volatility measure and the skew pertains to the nearest set of options, with maturity in excess of eight days.

Table 4.17: Regression results for the weekly option-implied skew and equity fund momentum from August 2007 to December 2010, defined in equation (4.3)..

η_t^3	Variable (mid-2007 to 2010)				
value	α	–0.1225	–0.1229	–0.0644	–0.1113
t-stat.		–16.9043	–17.2109	–2.6359	–11.7591
p-value		0	0	0.0091	0
	AR(1)	1.1490	1.1585	0.9712	1.1603
		18.2177	19.2969	78.0083	21.2947
		0	0	0	0
	AR(2)	–0.3007	–0.3083		–0.1817
		–3.0114	–3.2195		–3.4175
		0.0030	0.0015		0.0008
	AR(3)	0.1254	0.1236		
		2.1672	2.1734		
		0.0316	0.0311		
	MA(1)	–0.9922	–0.9925	–0.9157	–0.9880
		–116.655	–118.33	–26.9094	–103.7922
		0	0	0	0
	${}_N^m ff_{i,t}^e$	0.0190	0.01741	0.0104	0.0202
		5.7125	4.7651	2.4780	5.2706
		0	0	0.0142	0
	R_t		0.0021		
			1.1750		
			0.2416		
	VIX_t			–0.0021	
				–3.0264	
				0.0028	
	$ff_{i,t-1}^b$				–0.0310
					–1.7923
					0.0748
Adjusted R^2		0.3937	0.3970	0.3935	0.3919

Hypothesis 1 established that lagged bond flows were negatively related to skew in the pre-crisis period. Thereafter, bond flows revert to being positively contemporaneously related to skew. Hypothesis 2 has shown that the skew is positively related to current equity fund performance. In the post-crisis period, bond flows and equity flows were mildly negatively correlated. Performance Granger-caused bond flows. In the case of institutional equity fund flows, past own fund performance did not appear to generate such flows. There is however a slight positive contemporaneous correlation in the post-crisis period. An attempt to regress $ff_{i,t}^e$ on ${}_N ff_{i,t}^e$ over this period did not yield favourable results. Hence, institutional equity fund flows appear illusive. Testing for a unit root process over the entire period leads to a rejection of the null hypothesis of a unit root

Table 4.18: Regression results for the weekly option-implied skew and equity fund momentum from January 2005 to December 2010, defined in equation (4.3).

η_t^3	Variable	(2005–2010)			
value	α	–0.1380	–0.1377	–0.0641	–0.1334
t-stat.		–6.8038	–6.8489	–2.2088	–6.6792
p-value		0	0	0.0279	0
	AR(1)	0.9608	0.9596	0.9676	0.9587
		49.5332	47.4341	54.6083	46.8559
		0	0	0	0
	MA(1)	–0.8130	–0.8090	–0.8277	–0.8045
		–13.7724	–13.2842	–15.5394	–12.8333
		0	0.00	0	0
	${}_N^m ff_{i,t}^e$	0.0183	0.0169	0.0092	0.0198
		5.2836	4.3789	2.3156	5.5768
		0	0	0.0212	0
	R_t		0.0027		
			1.4013		
			0.1622		
	VIX_t			–0.0033	
				–2.7873	
				0.0057	
	$ff_{i,t-1}^b$				–0.0229
					–4.0764
					0.0001
Adjusted R^2		0.3413	0.3469	0.3695	0.3606

present.[30] Having briefly mentioned that the skew as well as TED spread Granger-causes $ff_{i,t}^e$, the following regressions will be evaluated over the sample periods to determine if either variable may be useful to forecast institutional investor equity fund flow:

$$ff_{i,t}^e \quad = \quad \alpha + \beta ff_{i,t-1}^e + \sum_{i=1}^{k} \gamma_i \eta_{t-i}^3 + \sum_{j=1}^{p} \lambda_j TED_{t-j} + \varphi_N ff_{i,t}^e + \epsilon_t, \tag{4.4}$$

where $k = 1,\ 2$ and $p = 0,\ 1,\ 2$ depend on the period. Equity fund performance and lagged TED may be omitted, as best regression results are displayed below. $ff_{i,t}^e$ is not persistent over the entire sample, however in the pre-crisis period, the lag coefficient is statistically significant. The results are reported in Tables 4.19, 4.20 and 4.21 for the relevant periods.

[30]The ADF test statistic of –19.06 and the associated one-sided p-value of 0.00 is smaller than the test critical values at the 1% (–3.45), 5% (–2.87) and 10% (–2.57) level.

Table 4.19: Regression results for the weekly institutional equity fund flows as a dependent variable from January 2005 to July 2007, defined in equation (4.4).

$ff^e_{i,t}$					
Sample	1/21/2005–7/27/2007				
Variable	Coefficient		Std. error	t-statistic	Prob.
α	0.2530		0.0622	4.0709	0.0001
η^3_{t-1}	1.3259		0.5860	2.2624	0.0253
AR(1)	–0.4176		0.0878	–4.75395	0
R-squared	0.1953	Mean dependent var			0.1294
Adjusted R-squared	0.1828	S.D. dependent var			0.7685
S.E. of regression	0.6947	Akaike info criterion			2.1319
Sum squared resid	62.2647	Schwarz criterion			2.1974
Log likelihood	–137.707	Hannan–Quinn criter.			2.1585
F-statistic	15.6502	Durbin–Watson stat			2.0950
Prob(F-statistic)	0				

Although the fit in this sample as indicated by the adjusted R^2 value in Table 4.19 is not very high and tends to decrease in the post-crisis period, the results indicate that an increase in the skew (becomes less negative) in week t leads to an increase in the subsequent weekly equity fund flows (as a percentage of NAV). Given that the flows are not measured in absolute USD values but are referenced relative to the NAV at the beginning of week t, it is the case that as institutional investors reduce their equity portfolio insurance, more capital is subsequently allocated to equity in week $t+1$. Hence, the skew may indeed be a leading indicator for global institutional investor sentiment. Positive consistent equity fund performance over the preceding four-week period tends to increase the skew in week t. In the pre-crisis period, this then leads to greater flows in the following week to equity funds. Since these flows as expressed as a percentage of NAV, an increase in the NAV will reduce the flow variable if the USD flow remains unchanged. Therefore, the numerator is likely to increase for this relationship to hold.

In Table 4.20, the results show an alternating relationship in the coefficient, consistent for both the skew and TED: $ff^e_{i,t+1}$ is positively (negatively) related to both skew and the TED spread in week t ($t-1$). The contemporaneous fund flow performance is included due to the slight positive correlation perceived in this period. The η^3_t regressions in Table 4.17 result in a negative AR(2) coefficient, and therefore this relationship is consistent with the alternating sign of coefficients here. Regardless, it is the week t coefficients which are both larger in magnitude and statistically

Table 4.20: Results for weekly institutional equity flows from August 2007 to December 2010, defined in equation (4.4).

$ff^e_{i,t}$				
Sample	7/27/2007–12/31/2010			
Variable	Coefficient	Std. error	t-statistic	Prob.
η^3_{t-1}	2.8020	0.8121	3.4502	0.0007
η^3_{t-2}	–2.2334	0.7329	–3.0474	0.0027
TED_{t-1}	0.0105	0.0036	2.957	0.0035
TED_{t-2}	–0.0078	0.0035	–2.2459	0.026
${}_Nff^e_{i,t}$	0.0604	0.0208	2.8990	0.0042
R-squared	0.1470	Mean dependent var		0.1537
Adjusted R-squared	0.1275	S.D. dependent var		1.023
S.E. of regression	0.9554	Akaike info criterion		2.7741
Sum squared resid	159.748	Schwarz criterion		2.8628
Log likelihood	–244.667	Hannan–Quinn criter.		2.8100
Durbin–Watson stat	1.9963			

more relevant for both skew and the TED spread. In essence, increased liquidity and skew in week t tends to result in greater equity fund flow in week $t+1$, which is accompanied by positive own fund performance.

Table 4.21: Regression results for weekly institutional equity flows defined using equation (4.4), from January 2005 to December 2010.

$ff^e_{i,t}$				
Sample	1/21/2005–12/31/2010			
Variable	Coefficient	Std. error	t-statistic	Prob.
η^3_{t-1}	2.3236	0.6084	3.8192	0.0002
η^3_{t-2}	–1.8778	0.5475	–3.4296	0.0007
TED_{t-1}	0.0091	0.0035	2.6173	0.0093
TED_{t-2}	–0.0064	0.0034	–1.8991	0.0585
${}_Nff^e_{i,t}$	0.0529	0.0191	2.7641	0.0061
R-squared	0.0919	Mean dependent var		0.1466
Adjusted R-squared	0.0800	S.D. dependent var		0.9224
S.E. of regression	0.8847	Akaike info criterion		2.6088
Sum squared resid	239.5096	Schwarz criterion		2.6690
Log likelihood	–400.673	Hannan–Quinn criter.		2.6329
Durbin–Watson stat	2.2478			

Over the entire sample period, the results in Table 4.21 are consistent with the post-crisis results in Table 4.20. Thus, $ff^e_{i,t}$ is clearly related to sentiment within US options markets. In fact, equity fund flows in week t seem to be determined by the level of the skew as well as those of liquidity in weeks $t-1$ and $t-2$. Own-fund performance does not appear to lead to fund flow; neither does equity fund flow result in positive equity fund performance. Hence, option-implied skew may well be a measure of forward-looking sentiment, given the relationship to institutional equity fund flows.

4.4 Conclusion and Practical Applications

This chapter has served to develop a theory of sentiment propagation which has yet to be examined using a novel data set; the chapter further contributes to literature by providing an empirical link between institutional investor sentiment, as measured by equity portfolio insurance, and dedicated USA equity and bond fund flows. The movement of fund flows globally has served to exacerbate financial crises, particularly in emerging markets during the 1990s. By examining global equity and bond fund flows at weekly frequencies, investors' risk appetite as well as preferences can be monitored. The source of fund flow data yields varying relationships between such flows and returns; thus caution is to be applied should momentum or contrarian strategies be developed to outperform a global index using country constituent indices.

Part I has established that sentiment propagation is tantamount to cross-border fund flows. Drawing upon diverse yet complementary strands of the finance literature, the relationships between financial markets, the macroeconomy and confidence have been explored. Cross-border and regional capital flows have been shown to be determined by global (US) as well as domestic fundamentals. Relative flows have also been used to enhance returns as a result of the feedback trader hypothesis. Empirical evidence which supports the use of fund flows as a sentiment measure for the relevant investor group within an economy is extensive. The integration of markets implies that sentiment within a given economy is likely to filter through to those countries which are linked via capital or trade flows to the source country. The focus of this research has been the former, with a particular emphasis on financial markets. Hence, cross-border capital fund flows are the most likely conduits for sentiment propagation.

Assuming this is to be the case, Part II has shown that US institutional portfolio insurance is consistent with flow-related variables. In particular, Hypothesis I has established that increases in weekly bond fund flows precede increases in portfolio insurance. Examining data over distinct periods allows for the adaptation of investor behaviour to different market regimes. The post-crisis period (the definition of this period includes the crisis) is characterised by flows into AE bonds and, in particular, capital repatriation to the US due to the 'flight-to-safety' phenomenon. During this period, it appears that it is in fact persistent positive equity performance which ultimately drives the desire or lack thereof, for portfolio insurance. Thus, Hypothesis 2 shows that an increase in the four-week rolling average of institutional equity fund performance tends to be accompanied by an increase in the skew over all sub-periods. This effect is in excess of that of institutional bond fund flows during the post-crisis period. As a corollary and most likely a significant ramification therefrom, the option-implied skew, alternatively considered a forward-looking sentiment measure, has been shown to Granger-cause institutional equity fund flows. Given that the aggregation of US and non-US domiciled funds are considered a global institutional investor sentiment measure, it is then the case that the index options markets contain forward-looking information pertaining to equity fund flow. In conclusion, the option-implied skew appears to contain both lagged and forward-looking information pertaining to institutional bond and equity fund flows of globally domiciled investors. The response of portfolio insurance (skew) is dependent on market regimes and the macroeconomic environment, as captured by the VIX and TED spread. Therefore, institutional portfolio insurance appears to be that all-encompassing measure of global investor sentiment given the perceived relationships with dedicated US bond fund flows, equity performance and equity flows.

This chapter has shown explicitly the link between institutional investor sentiment as measured by the third robust moment, and the global dedicated USA bond and equity flows. Thus, monitoring the nearest maturity index options provides insight into the movement into such equity funds. At the same time, the bond fund flows of institutional investors preempt an increase in portfolio insurance. This is conditional on market regime, dictated by the VIX and TED spread. Thus identifying the market regime is a cursory means to establish whether bond or equity fund flows can in face be used to provide a forecast of the movement on the moments of the RND and therefore, the relative cheapness of certain options. Thus, as mentioned in §3.7, superior information based on fund flows as well as macro data releases can be used to find options which appear underpriced prior to the release of the information within the public domain.

Chapter 5

Conclusion

5.1 Summary and Conclusion

This thesis has presented a number of implications of investor behaviour to financial markets. Although this field of finance in parlance relates to individual behavioural biases, of relevance is aggregate behaviour, and therefore the associated sentiment of a particular investor group. This thesis has aspired to formalise a theory of sentiment propagation across financial markets. Although much research alludes to the integration of financial markets and the real economy, there have been few attempts to provide a robust framework in which to establish the effect of sentiment in those identified relationships. The expanse and content of the literature dictates the complexity; yet the pertinence of such a framework is clear. Considering both macro sentiment and investor sentiment measures, this thesis has professed the channels through which both are likely to propagate across borders, thereby influencing behaviour of the recipient domicile. Yet feedback effects are also likely to be incurred – this has not been addressed here. The contributions of this research have been to corroborate the use of macro sentiment as a leading indicator, and to address sentiment propagation.

In particular, the information content of macro sentiment which is inaccessible though macro fundamental data has appeared to be a useful leading indicator for financial instability. Fundamental data which highlight imbalances within an economy are useful, however the complexity of these systemic events is non-trivial and further compounded by the inability to identify all sources of risk. Chapter 2 has shown that macro sentiment conveys expectations regarding the future course of the economy, over and above those of related economic time series. Additionally, the relationship that exists between bilateral trade partners is evident within macro sentiment.

Analogous to the instance of bank runs which often arise from widespread panic independent of fundamentals, systemic crises are subject to the coalescence of these forces. Countries are increasingly integrated through both trade and financial markets. The effect of capital mobility exacerbated the effects of the global financial crisis in 2008 given the volatility and direction of flow. Financial contagion which is closely tied to sentiment propagation is therefore of consequence as systemic crises are not constrained by nations' borders: Fund flows are the channels through which investors' beliefs and risk appetite are transmitted. The flight-to-safety phenomenon characterised global fund flows during this period; the recovery saw shifts in behaviour as investors' redirected capital to emerging markets. Global sentiment is dictated by the largest economy, as the VIX and the TED are those common shocks emanating from the US which affected flows. Considering this dominance, dedicated US equity and bond flows of both US and non-US domiciled investors necessarily embody global sentiment. Thus, establishing the connection between institutional portfolio insurance and that of global sentiment serves to reinforce the former as a measure of investor sentiment.

The assumption that trading activity within index options markets embodies institutional investor sentiment serves as the basis for the empirical analysis in Chapter 3. Examining the dynamics of daily option-implied measures and returns results in the skew which is consistent with those other measures, and robust across time periods. Hence this is the reference measure used within Chapter 3. Survey-related sentiment measures have been shown to be Granger-caused by global common risk factors which is analogous to macro sentiment with respect to economically relevant data. However, the investor sentiment survey result is derived from the difference between bullish and bearish investors. The alternative methods in construction between macro and investor sentiment should render the former more informative.

This thesis has served to identify relationships between various measures of sentiment as defined in Chapters 3 and 4. Although there is an extensive body of research which seeks to empirically validate the use of selected sentiment measures in the context of aggregate market reversals, it is fundamentally challenging to accurately identify mispricings. In the cross-section, sentiment is an additional factor which is likely to affect stocks, much like the factors of Fama & French (1996), and the momentum factor of Carhart (1997). The effects of investor sentiment extend beyond financial markets. In the extreme, the financial markets suffer consequences equivalent to natural disasters. Systemic crises tend to impose heavily on real economic activity in the medium and long term. In some instances, the distortions endure for extended periods as macro sentiment remains subdued. The affected consumers are those that both perceive and are afflicted by impending crises. Thus, behavioural finance commences and concludes at the individual level.

5.2 Further Research

Having explored the concept of sentiment within real and financial markets, the relevance thereof is unequivocal. The use of sentiment is twofold: in addition to option trading strategies which exploit information regarding sentiment derived from the index RND, fund flow data which have been identified as the medium through which sentiment propagates, can be used within signalling methods to detect pending financial instability, as discussed in chapter 2. Financial deregulation and the lack of capital controls have created an environment whereby capital movement has the ability to destabilise markets. Hence, contagion between financial markets may be accounted for using cross border equity or bond fund flows since financial instability within a country may arise due to external influences. Thus, research which incorporates the effects of sentiment as well as financial contagion should be addressed. Regulatory research which optimises the efficient functioning of financial markets would also benefit therefrom.

Appendix

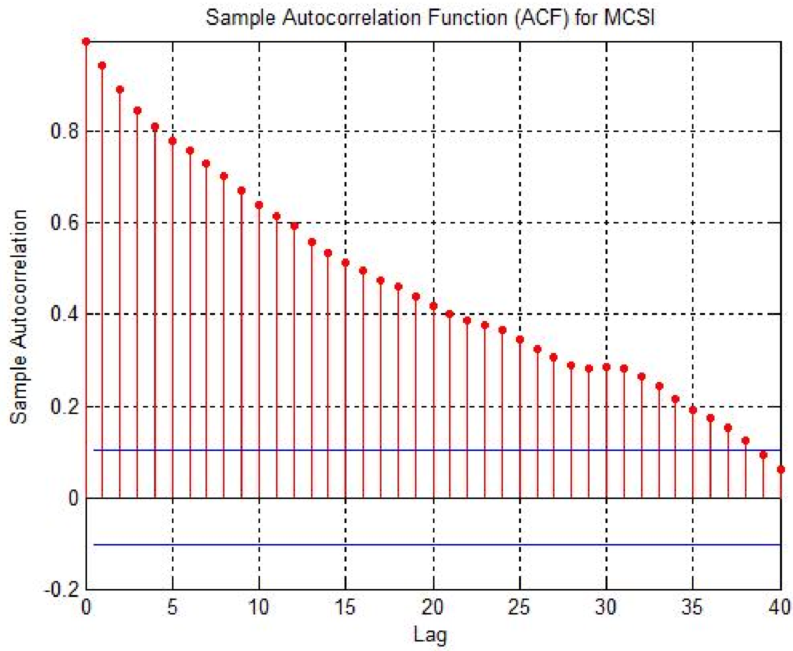

Figure 5.1: The autocorrelation function for the monthly CS^{US} series from January 1960 to December 2008.

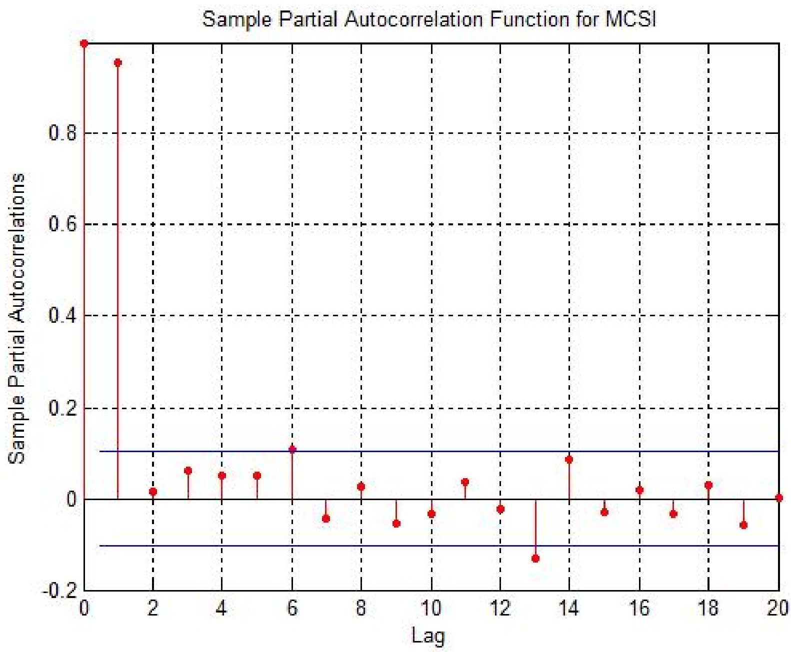

Figure 5.2: The partial-autocorrelation function for the monthly CS^{US} series from January 1960 to December 2008.

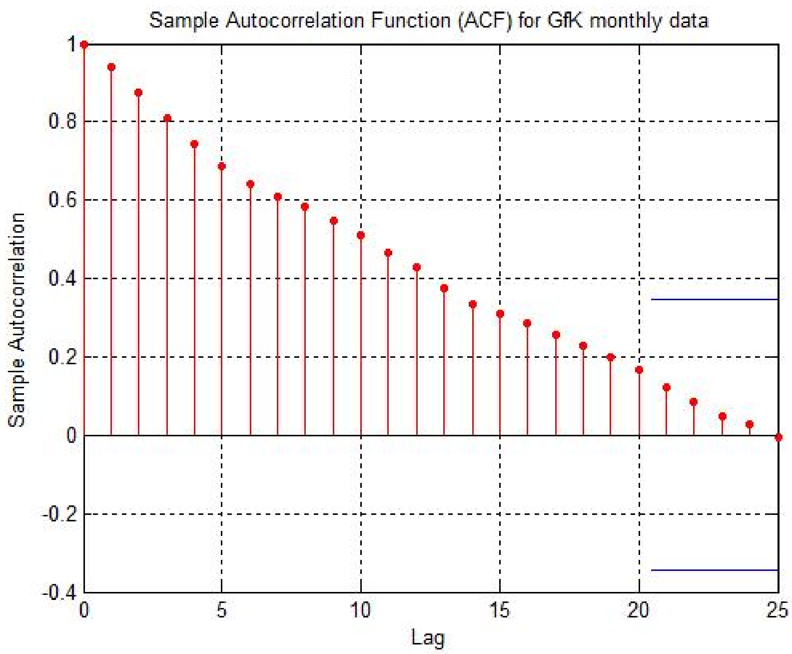

Figure 5.3: The autocorrelation function for the monthly CS^{UK} series from January 1974 to December 2008.

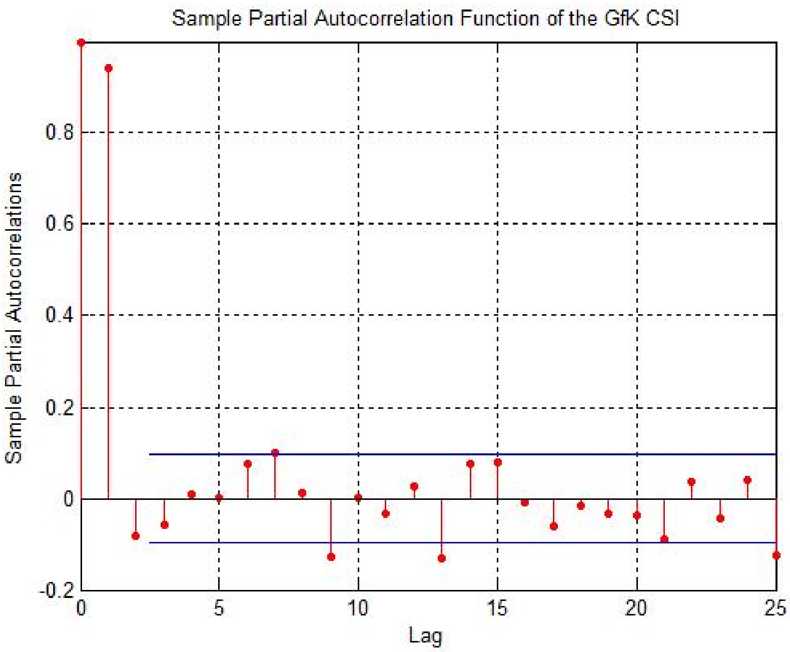

Figure 5.4: The partial-autocorrelation function for the monthly CS^{UK} series from January 1974 to December 2008.

Table 5.1: Granger causality for monthly CS^{UK}, CS^{US} and trade strength for both the US and UK over the period January 1974 to December 2008, and January 1990 to December 2008.

Sample period (six lags)	1974m01	– 2008m12	1990m01	– 2008m12
Null hypothesis	F-statistic	Prob.	F-statistic	Prob.
CS^{US} does not Granger cause CS^{UK}	2.2651	0.0367	5.1281	6.00E-05
T^{UK} does not Granger cause CS^{UK}	2.9270	0.0083	3.8727	0.0011
CS^{UK} does not Granger cause T^{UK}	1.2489	0.2803	2.0664	0.0585
T^{UK}_{US} does not Granger cause CS^{UK}	1.8853	0.0821	2.9538	0.0087
T^{UK} does not Granger cause CS^{US}	2.4184	0.0262	3.1178	0.0060
T^{US}_{UK} does not Granger cause CS^{US}	2.5142	0.0212	1.6418	0.1371
T^{UK}_{US} does not Granger cause T^{UK}	6.3323	2.00E-06	4.4130	0.0003
T^{UK} does not Granger cause T^{UK}_{US}	7.3879	2.00E-07	5.9315	1.00E-05
T^{US} does not Granger cause T^{UK}	3.7450	0.0012	5.0150	8.00E-05
T^{US}_{UK} does not Granger cause T^{UK}	3.5990	0.0017	2.5766	0.0198
T^{UK} does not Granger cause T^{US}_{UK}	4.2520	0.0004	4.3804	0.0003
T^{US} does not Granger cause T^{UK}_{US}	6.6900	9.00E-07	7.5701	2.00E-07
T^{UK}_{US} does not Granger cause T^{US}	3.7244	0.0013	3.0260	0.0074
T^{US}_{UK} does not Granger cause T^{US}	2.0004	0.0646	2.2893	0.0367
T^{US} does not Granger cause T^{US}_{UK}	3.5079	0.0022	9.7481	2.00E-09

Table 5.2: Granger causality for monthly CS^{UK}, CS^{US} and trade strength for both the US and UK over the period January 1990 to December 2008.

Correlation	CS^{UK}	CS^{US}	T^{UK}	T^{UK}_{US}	T^{US}	T^{US}_{UK}
CS^{UK}	1					
CS^{US}	0.71	1				
T^{UK}	0.15	0.26	1			
T^{UK}_{US}	–0.14	–0.36	–0.51	1		
T^{US}	–0.21	0.058	0.72	–0.67	1	
T^{US}_{UK}	–0.11	0.15	0.54	–0.79	0.75	1

Table 5.3: US quarterly data to identify threshold values for indicators.

Year	$p_{g,t}^{US}$	$e_{g,t}^{US}$	$h_{g,t}^{US}$	$c_{g,t}^{US}$
1984Q1	–1.4%	3.1%	0.3%	18.3%
1984Q2	–0.2%	–2.2%	0.5%	10.3%
1984Q3	0.7%	3.2%	0.8%	8.7%
1984Q4	2.4%	1.8%	1.4%	2.0%
1985Q1	2.4%	6.5%	1.8%	–0.4%
1985Q2	3.1%	8.3%	1.9%	–2.0%
1985Q3	2.9%	0.6%	2.4%	–4.3%
1985Q4	4.1%	11.1%	2.6%	–6.3%
1986Q1	2.9%	17.9%	2.9%	–2.6%
1986Q2	3.6%	16.6%	4.2%	–2.2%
1986Q3	3.4%	3.5%	4.6%	–4.5%
1986Q4	4.0%	4.2%	5.3%	–7.0%
1987Q1	2.1%	16.3%	6.7%	–7.9%
1987Q2	1.8%	12.8%	6.4%	–6.1%
1987Q3	1.1%	11.5%	5.1%	–3.8%
1987Q4	–0.4%	–14.6%	3.7%	–10.0%
1988Q1	–0.7%	–11.0%	2.3%	–3.5%
1988Q2	–1.0%	–7.5%	3.1%	–2.0%
1988Q3	–1.2%	–9.1%	2.0%	0.2%
1988Q4	–1.4%	–8.0%	0.7%	–2.7%
2003Q1	0.1%	–19.2%	1.4%	–8.8%
2003Q2	0.5%	–3.9%	2.0%	2.6%
2003Q3	–1.0%	0.7%	2.6%	3.3%
2003Q4	–1.3%	12.4%	3.1%	6.3%
2004Q1	–1.8%	12.4%	2.8%	11.5%
2004Q2	–1.6%	11.7%	3.4%	5.6%
2004Q3	–1.2%	8.6%	4.1%	7.2%
2004Q4	–0.6%	15.1%	3.7%	4.7%
2005Q1	–1.5%	10.1%	4.0%	4.3%
2005Q2	–0.2%	8.5%	4.2%	0.2%
2005Q3	0.1%	8.9%	3.7%	–2.0%
2005Q4	0.8%	8.4%	2.7%	–6.1%
2006Q1	0.3%	9.5%	0.9%	1.5%
2006Q2	1.4%	4.5%	–1.6%	–3.1%
2006Q3	2.0%	7.2%	–3.9%	–1.9%
2006Q4	2.2%	11.3%	–4.5%	6.9%
2007Q1	1.6%	7.6%	–6.3%	5.6%
2007Q2	1.8%	8.5%	–8.3%	–0.1%
2007Q3	1.9%	6.9%	–9.2%	–1.0%
2007Q4	1.9%	0.7%	–12.6%	–8.4%

Table 5.4: Granger causality using two lags for gaps over the period 1960Q1 to 2009Q2 (updated data included two additional quarters).

Null hypothesis	F-statistic	Prob.
$e_{g,t}^{US}$ does not Granger cause $c_{g,t}^{US}$	16.5140	2.00E-07
$c_{g,t}^{US}$ does not Granger cause $e_{g,t}^{US}$	2.70738	0.0693
$c_{g,t}^{US}$ does not Granger cause $p_{g,t}^{US}$	5.2406	0.0061
$h_{g,t}^{US}$ does not Granger cause $c_{g,t}^{US}$	2.5877	0.0778
$e_{g,t}^{US}$ does not Granger cause $p_{g,t}^{US}$	3.8602	0.0227
$e_{g,t}^{US}$ does not Granger cause $h_{g,t}^{US}$	2.7114	0.0690

Table 5.5: Quarterly gaps for series indicated prior to crises within the UK. The macro sentiment series has been shifted by +100 index points.

Year	$p_{g,t}^{UK}$	$e_{g,t}^{UK}$	$h_{g,t}^{UK}$	$c_{g,t}^{UK}$
2003Q1	13%	–31%	18%	–10%
2003Q2	9%	–32%	18%	–6%
2003Q3	10%	–24%	17%	–4%
2003Q4	12%	–17%	16%	–6%
2004Q1	22%	–12%	15%	–3%
2004Q2	16%	–10%	17%	–3%
2004Q3	22%	–11%	16%	–5%
2004Q4	16%	–5%	11%	–4%
2005Q1	23%	0%	8%	1%
2005Q2	17%	3%	7%	–1%
2005Q3	25%	7%	5%	–3%
2005Q4	24%	9%	2%	–7%
2006Q1	33%	15%	1%	–3%
2006Q2	38%	19%	2%	–2%
2006Q3	29%	13%	2%	–3%
2006Q4	27%	14%	1%	–3%
2007Q1	36%	14%	1%	–3%
2007Q2	36%	15%	2%	1%
2007Q3	48%	15%	1%	–1%
2007Q4	48%	11%	–1%	–5%

Table 5.6: Granger causality using two lags for quarterly gaps in the UK over the period 1974Q1 to 2009Q4 (updated data increased observations).

Null hypothesis	F-statistic	Prob.
$e_{g,t}^{UK}$ does not Granger cause $p_{g,t}^{UK}$	2.7818	0.0654
$c_{g,t}^{UK}$ does not Granger cause $e_{g,t}^{UK}$	3.2243	0.0428
$e_{g,t}^{UK}$ does not Granger cause $c_{g,t}^{UK}$	3.0945	0.0485
$h_{g,t}^{UK}$ does not Granger cause $e_{g,t}^{UK}$	2.6709	0.0728
$h_{g,t}^{UK}$ does not Granger cause $c_{g,t}^{UK}$	4.3396	0.0149
$c_{g,t}^{UK}$ does not Granger cause $h_{g,t}^{UK}$	2.7987	0.0644

References

Äijö, J. (2008), 'Impact of US and UK macroeconomic news announcements on the return distribution implied by the FTSE-100 index options', *International Review of Financial Analysis* **17**(2), 242–258.

Alonso, F., Blanco, R. & Rubio, G. (2006), 'Option-implied preferences adjustments, density forecasts, and the equity risk premium', Banco de España working papers, Banco de España.

Amin, K., Coval, J. D. & Seyhun, H. N. (2004), 'Index option prices and stock market momentum', *The Journal of Business* **77**(4), 835–874.

Ammer, J. & Mei, J. (1996), 'Measuring international economic linkages with stock market data', *The Journal of Finance* **51**(5), 1743–1763.

Bahra, B. (1997), 'Implied risk-neutral probability dentisty functions from option prices: theory and application', `http://www.bankofengland.co.uk/publications/workingpapers/wp66.pdf`. Bank of England working paper.

Baker, M. & Wurgler, J. (2006), 'Investor sentiment and the cross-section of stock returns', *Journal of Finance* **61**(4), 1645–1680.

Baker, M. & Wurgler, J. (2004), 'Investor sentiment in the stock market', *Journal of Financial Markets* **7**(3), 271–299.

Baker, M., Wurgler, J. & Yuan, Y. (2011), 'Global, local, and contagious investor sentiment', `http://www.dallasfed.org/institute/wpapers/2009/0037.pdf`. Federal Reserve Bank of Dallas, Globalization and Monetary Policy Institute, Working Paper No. 37.

Bakshi, G. & Chen, Z. (2005), 'Stock valuation in dynamic economies', *Journal of Financial Markets* **8**(2), 111–151.

Bakshi, G., Kapadia, N. & Madan, D. (2003), 'Stock return characteristics, skew laws, and the differential pricing of individual equity options', *The Review of Financial Studies* **16**(1), 101–143.

Bakshi, G., Kapadia, N. & Madan, D. (2000), 'Spanning and derivative-security valuation', *Journal of Financial Economics* **55**(2), 205–238.

Bandopadhyaya, A. & Jones, A. L. (2006), 'Measuring investor sentiment in equity markets', *Journal of Asset Management* **7**(3), 208–215.

Barberis, N., Shleifer, A. & Vishny, R. W. (1997), 'A model of investor sentiment', `http://www.nber.org/papers/w5926`. NBER working paper series.

Bates, D. S. (2003), 'Empirical option pricing: a retrospection', *Journal of Econometrics* **116**(1), 387-404.

Bell, J. & Pain, D. (2000), 'Leading indicator models of banking crises – a critical review'. Bank of England, Financial Stability Review.

Ben-Rephael, A., Kandel, S. & Wohl, A. (2010), 'Measuring investor sentiment with mutual fund flows'. *Journal of Financial Economics*, in press, corrected proof.

Bebera, A. & Brandt, M. W. (2006), 'The effect of macroeconomic news on beliefs and preferences: Evidence from the options market', *The Journal of Monetary Economics* **53**(8), 1997–2039.

Berry, S. & Davey, M. (2004), 'How should we think about consumer confidence?', `http://www.bankofengland.co.uk/publications/quarterlybulletin/qb040301.pdf`. Bank of England, Quarterly Bulletin.

Bhardwaj, G., Hamilton, D. J. & Ameriks, J. (2011), 'Hedging inflation: The role of expectations', `https://personal.vanguard.com/pdf/icruih.pdf`. Vanguard research.

Bingham, N. & Kiesel, R. (2004), *Risk-Neutral Valuation: Pricing and Hedging of Financial Derivatives*, second edn, Springer.

Black, F. & Scholes, M. (1973), 'The pricing of options and corporate liabilities', **73**(May–June), 637–659.

Bollen, N. P. B. & Whaley, R. E. (2004), 'Does net buying pressure affect the shape of implied volatility functions?', *The Journal of Finance* **59**(2), 711–753.

Bondarenko, O. (2000), 'Recovering risk-neutral densities: a new nonparametric approach', http://papers.ssrn.com/sol3/papers.cfm?abstract_id=246063. EFA 2000.

Bondarenko, O. (2003), 'Estimation of risk-neutral densities using positive convolution approximation', *Journal of Econometrics* **116**(1-2), 85–112.

Bordo, M., Eichengreen, B., Klingebiel, D., Martinez-Peria, M. S. & Rose, A. K. (2001), 'Is the crisis problem growing more severe?', *Economic Policy* **16**(32), 53–82.

Borio, C. (2006), 'Monetary and financial stability: Here to stay?', *The Journal of Banking and Finance* **30**(12), 3407–3414.

Borio, C. & Drehmann, C. M. (2009), 'Assessing the risk of banking crises – revisited', http://www.bis.org/publ/qtrpdf/r_qt0903e.pdf. BIS Quarterly Review.

Borio, C. & Lowe, P. (2002), 'Asset prices, financial and monetary stability: Exploring the nexus', http://www.bis.org/publ/work114.pdf?noframes=1. BIS Working Paper No. 114s.

Boyd, J., De Nicolò, G. & Loukoianova, E. (2009), 'Banking crises and crisis dating: Theory and evidence', http://www.iadb.org/intal/intalcdi/PE/2009/03912.pdf. IMF Working Paper, WP/09/141.

Breeden, D. & Litzenberger, R. (1978), 'Prices of state-contingent claims implicit in option prices', *Journal of Business* **51**, 621–651.

Brown, G. W. & Cliff, M. T. (2004), 'Investor sentiment and the near-term stock market', *The Journal of Empirical Finance* **11**(1), 1–27.

Brown, G. W. & Cliff, M. T. (2005), 'Investor sentiment and asset valuation', *The Journal of Business* **78**(2), 405–440.

Caprio, G. & Klingebiel, D. (1999), 'Episodes of systemic and borderline financial crises'. Washington, DC: World Bank Mimeo.

Carhart, M. M. (1997), 'On persistence in mutual fund performance', *The Journal of Finance* **52**(1), 57–82.

Chan, C., Faff, R. W. & Hwang, C. (2009), 'Sentiment contagion, corporate governance, information and legal environments'. Massey University, University of Queensland, Nanyang Technological University (NTU).

Charles D. Delorme Jr, Kamerschen, D. R. & Voeks, L. F. (2001), 'Consumer confidence and rational expectations in the United States compared with the United Kingdom', *Applied Economics* **33**(7), 863–869.

Chen, J., Hong, H. & Stein, J. C. (2002), 'Breadth of ownership and stock returns', *Journal of Financial Economics* **66**(2-3), 171–205.

Chen, N. & Ross, R. R. S. A. (1986), 'Economic forces and the stock market', *Journal of Business* **59**(3), 383–403.

Chicago Board Options Exchange (2009), 'The CBOE volatility index – VIX', `http://www.cboe.com/micro/vix/vixwhite.pdf`. VIX, Index White Paper.

Clarke, R. G. & Statman, M. (1998), 'Bullish or bearish?', *Financial Analysts Journal* **54**(3), 63–72.

Cogley, T. & Nason, J. M. (1995), 'Effects of the Hodrick–Prescott filter on trend and difference stationary time series', *Journal of Economic Dynamics and Control* **19**(1-2), 253–278.

Crockett, A. (2003), 'International standard setting in financial supervision'. General Manager of the BIS and Chairman of the Financial Stability Forum, Lecture at the Cass Business School.

Curtin, R. (2007), 'Consumer sentiment surveys: Worldwide review and assessment'. Director Surveys of Consumers, University of Michigan, *Journal of Business Cycle Measurement and Analysis*.

Davis, E. P. & Karim, D. (2008), 'Comparing early warning systems for banking crises', *Journal of Financial Stability* **4**(2), 89–120.

De Long, J. B., Shleifer, A., Summers, L. H. & Waldmann, R. J. (1990), 'Noise trader risk in financial markets', *Journal of Political Economy* **98**(4), 703–738.

Demirgüç-Kunt, A. & Detragiache, E. (2005), 'Cross-country empirical studies of systemic bank distress: A survey', *National Institute of Economic Review* **192**(1), 68–83.

Dennis, P. & Mayhew, S. (2002), 'Risk-neutral skewness: Evidence from stock options', *Journal of Financial and Quantitative Analysis* **37**(3), 471–493.

Derman, E. & Kani, I. (1994), 'Riding on a smile', **7**(2).

Diamond, D. W. & Dybvig, P. H. (1983), 'Bank runs, deposit insurance and liquidity', *Journal of Political Economy* **91**(3), 401–419.

Dickinson, D. G. (2010), 'Stock market integration and macroeconomic fundamentals: An empirical analysis, 1980–95', *Applied Financial Economics* **10**(3), 261–276.

Dupire, B. (1994), 'Pricing with a smile', *Risk* **7**(1).

Easaw, J. & Ash, C. (2004), 'Sentimental, rational and useful? A directional analysis of consumer sentiment surveys in the US and the UK'. Department of Economics, The University of Reading Business School; Cardiff Business School, University of Wales, Aberconway Building.

Easaw, J. & Ghoshraya, A. (2008), 'The cyclical nature of consumer sentiments indices in the US and UK', *Journal of Socio-Economics* **37**(5), 1994–1998.

Edgerton, Louis. H. & Lee, Jae. Ha. (1996), 'The Creation and Resolution of Market Uncertainty: The Impact of Information Releases on Implied Volatility', *Journal of Financial and Quantitative Analysis* **31**(4), 513–539.

Edelen, R. M. & Warner, J. B. (2001), 'Aggregate price effects of institutional trading: a study of mutual fund flow and market returns', *Journal of Financial Economics* **59**(2), 195–220.

Fama, E. (1997), 'Market efficiency, long-term returns, and behavioural finance', *Journal of Financial Economics* **49**(3), 283–3067.

Fama, E. F. & French, K. R. (1996), 'Multifactor explanations of asset pricing anomalies', *Journal of Finance* **51**(1), 55–84.

Finucane, M. L., Slovic, P., Mertz, C. K., Flynn, J. & Satterfield, T. A. (2000), 'Gender, race, and perceived risk: The 'white male' effect', *Healthy Risk and Society* **2**(2), 159–172.

Fisher, K. L. & Statman, M. (2003), 'Consumer confidence and stock returns', *Journal of Portfolio Managment* **30**(1), 115–127.

Fisher, K. L. & Statman, M. (2000), 'Investor sentiment and stock returns', *Financial Analysts Journal* **56**(2), 16–23.

Flannery, M. J. & Protopapadakis, A. A. (2002), 'Macroeconomic factors do influence aggregate stock returns', *Review of Financial Studies* **15**(3), 751–782.

Forbes, K. J. & Rigobon, R. (2002), 'No contagion, only interdependence: Economic perspectives easing stock market comovements', *Journal of Finance* **57**(5), 2223-2261.

Fornani, F. & Mele, A. (2001), 'Volatility smiles and the information content of news', *Applied Financial Economics* **11**, 179-186.

Fratzscher, M. (2011), 'Capital flows, push versus pull factors and the global financial crisis'. European Central Bank, Working Paper Series No. 1364.

French, K. R. & Poterba, J. M. (1991), 'Investor diversification and international equity markets', *The American Economic Review* **81**(2), 222–226.

Fuhrer, J. C. (1993), 'What role does consumer sentiment play in the U.S. macroeconomy?'. *New England Economic Review*.

Gemmill, G. & Saflekos, A. (2000), 'How useful are implied distributions? Evidence from stock index options', *Journal of Derivatives* **7**(3), 83–91.

Giot, P. (Spring 2005), 'Relationships between implied volatility indexes and stock index returns', *Journal of Portfolio Management* **31**(3), 92–100.

Greenspan, A. (1996), 'The challenge of central banking in a democratic society', `http://www.federalreserve.gov/boarddocs/speeches/1996/19961205.htm`. Annual Dinner and Francis Boyer Lecture of The American Enterprise Institute for Public Policy Research, Washington, DC.

Hakkio, C. S. & Keeton, W. R. (2009), 'Financial stress: What is it, how can it be measured, and why does it matter?'. Economic Review, Federal Reserve Bank of Kansas City (Second Quarter).

Han, B. (2007), 'Investor sentiment and option prices', *Review of Financial Studies* **21**(1), 387–414.

Hansis, A., Schlag, C. & Vilkov, G. (2010), 'The dynamics of risk-neutral implied moments: evidence from individual options', `http://ssrn.com/abstract=1470674`. Goethe University Frankfurt – House of Finance.

Harvey, A. C. & Jaeger, A. (1993), 'Detrending, stylized facts and the business cycle', *Journal of Applied Econometrics* **8**(3), 231–247.

Hodrick, R. J. & Prescott, E. C. (1997), 'Postwar U.S. business cycles: An empirical investigation', *Journal of Money, Credit and Banking* **29**(1), 1–16.

IMF World Economic Outlook (1998), 'Financial crises: causes and indicators'. World Economic and Financial Surveys.

Indro, D. C. (2004), 'Does mutual fund flow reflect investor sentiment?', *The Journal of Behavioural Finance* **5**(2), 105–115.

Jank, S. (2011), 'Mutual fund flows, expected returns, and the real economy'. CFR Working Papers 11-04, University of Cologne, Centre for Financial Research.

Jansen, W. J. & Nahuis, N. J. (2003), 'The stock market and consumer confidence: European evidence', *Economic Letters* **79**(1), 89–98.

Kaminsky, G. L. & Reinhart, C. M. (1999), 'The twin crises: The causes of banking and balance-of-payments problems', *The American Economic Review* **89**(3), 473–500.

Katona, G. (May 1968), 'Consumer behavior: Theory and findings on expectations and aspirations', *The American Economic Review* **58**(2), 19–30.

Kydland, F. E. & Prescott, E. C. (1990), 'Business cycles: Real facts and a monetary myth', *Federal Reserve Bank of Minneapolis Quarterly Review* **14**(2), 1–17.

Laeven, L. & Valencia, F. (2008), 'Systemic banking crises: A new database'. IMF Working Paper, WP/08/224.

Lee, C. M. C., Shleifer, A. & Thaler, R. H. (1990), 'Closed-end mutual funds', *The Journal of Economic Perspectives* **4**(4), 153–164.

Lee, W. Y., Jiang, C. X. & Indro, D. C. (2002), 'Stock market volatility, excess returns, and the role of investor sentiment', *Journal of Banking and Finance* **26**(12), 2277–2299.

Lemmon, M. & Ni, S. X. (2008), 'The effects of investor sentiment on speculative trading and prices of stock'. `http://ssrn.com/abstract=1306237`.

Matsusaka, J. G. & Sbordone, A. M. (1995), 'Consumer confidence and economic fluctuations', *Economic Inquiry* **33**(2), 296-318.

Meyer, B., Anamootoo, J. & Schmitz, I. (2006), 'Predictive power of weekly fund flows'. Deutsche Bank, Europe, Macro Strategy.

Mishkin, F. S., Hall, R., Shoven, J., Juster, T. & Lovell, M. (1978), 'Consumer sentiment and spending on durable goods', *Brookings Papers on Economic Activity*, 1, 217–232.

Neal, R. & Wheatley, S. M. (1998), 'Do measures of investor sentiment predict returns?', *The Journal of Financial and Quantitative Analysis* **33**(4), 523–547.

Newey, W. K. & West, K. D. (1987), 'A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix', *Econometrica* **55**(3), 703–708.

Olsen, R. A. & Cox, C. M. (2001), 'The influence of gender on the perception and response to investment risk: The case of professional investors', *The Journal of Psychology and Financial Markets* **2**(1), 29–36.

Otoo, M. W. (1999), 'Consumer sentiment and the stock market'. Board of Governers of the Federal Reserve System.

Pain, N. & Weale, M. (2001), 'The information content of consumer surveys', *National Institute Economic Review* **178**(1), 44–47.

Ratanapakorn, O. & Sharma, S. C. (2007), 'Dynamic analysis between the US stock returns and the macroeconomic variables', *Applied Financial Economics* **17**(5), 369–377.

Ravn, M. O. & Uhlig, H. (1997), 'On adjusting the H-P filter for the frequency of observations', `http://arno.uvt.nl/show.cgi?fid=3560`. Tilburg University, Center for Economic Research in its series Discussion Paper No. 1997-50.

Rehman, Z. & Vilkov, G. (2010), 'Risk-neutral skewness: Return predictability and its sources', `http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1301648`. BlackRock, Goethe University Frankfurt – Department of Finance.

Reinhart, C. M. & Rogoff, K. S. (2008), 'This time is different: A panoramic view of eight centuries of financial crises'. NBER Working Paper No. 13882.

Rizova, S. (2010), 'Predictable returns of trade-linked countries: Evidence and explanations'. University of Chicago Booth School of Business.

Ross, S. A. (1976), 'The arbitrage theory of capital asset pricing', **13**, 341–360.

Rubinstein, M. (1994), 'Implied binomial trees', **49**(3), 771–818.

Schinasi, G. J. (2004), 'Defining financial stability'. IMF Working Paper, WP/04/187.

Schmeling, M. (2009), 'Investor sentiment and stock returns: Some international evidence', *Journal of Empirical Finance* **16**(3), 394–408.

Shefrin, H. (1999), 'Irrational exuberance and option smiles', *Financial Analysts Journal* **55**(6), 91–103.

Shiller, R. J. (1997), 'Why do people dislike inflation?', `http://www.nber.org/papers/w5539.pdf?new_window=1`. NBER Working Paper Series, No 5539.

Shleifer, A. & Vishny, R. W. (1997), 'The limits of arbitrage', *The Journal of Finance* **52**(1), 35–55.

Simon, D. P. & Wiggins III, R. A. (2001), 'S&P futures returns and contrary sentiment indicators', *Journal of Futures Markets* **21**(5), 447462.

Solt, M. E. & Statman, M. (1988), 'How useful is the sentiment index?', *Financial Analysts Journal* **44**(5), 45–55.

Survey Research Center (2010), 'Survey of consumers', `http://www.sca.isr.umich.edu/documents.php?c=i`. University of Michigan.

Thorp, W. A. (2004), 'Investor sentiment as a contrarian indicator', `http://www.aaii.com/files/sentimentCIfeature.pdf`. The American Association of Individual Investors.

Throop, A. W. (1992), 'Consumer sentiment: Its causes and effects', `http://www.frbsf.org/publications/economics/review/1992/92-1_35-59.pdf`. Federal Reserve Bank of San Fransisco.

Wang, Y.-H., Keswani, A. & Taylor, S. J. (2006), 'The relationships between sentiment, returns and volatility', *International Journal of Forecasting* **22**, 109–123.

Warther, V. A. (1995), 'Aggregate mutual fund flows and security returns', *Journal of Financial Economics* **39**(2-3), 209–235.

Whaley, R. E. (2008), 'Understanding VIX'. Vanderbilt University – Owen Graduate School of Management.

Xing, Y., Zhang, X. & Zhao, R. (2008), 'What does individual option volatility smirk tell us about future equity returns?', http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1107464. AFA 2009 San Francisco Meetings Paper.