Investor Sentiment as a Factor in an APT Model: An International Perspective Using the FEARS Index

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DECLARATION

I, Kamini Solanki, declare that this thesis is my own unaided work. It is submitted in fulfilment of the requirements for the degree of Master of Commerce (M.Com) in Finance at the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination at this or any other university.

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"No one who achieves success does so without acknowledging the help of others. The wise and confident acknowledge this help with gratitude."

~ Alfred North Whitehead

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Definitions of Terms and Abbreviations

Abreast of the Market (AOTM) – A column in the Wall Street Journal focusing purely on financial news.

Arbitrage Pricing Theory (APT) – A theory of asset pricing that posits that the expected return of a financial asset can be modelled as a linear function of various factors, either macro- or micro-economic in nature.

American Association of Independent Investors (AAII) – The AAII conducts a weekly survey of its member and their view of future market direction, specifically the survey asks members whether they have a bullish, bearish or neutral outlook on the stock market over the next six months.

Animus X – The survey focuses on the prospects of the German stock market over the short-term and medium-term, where short-term sentiment concerns expectations for the following week and medium term sentiment covers respondents' expectation over the next three months.

Capital Asset Pricing Model (CAPM) – A model that describes the relationship between risk and expected return that is used to price risky assets.

FNB/BER Consumer Confidence Index (CCI) – A survey-based sentiment index compiled by the Bureau of Economic Research in Stellenbosch, South Africa. The survey is constructed using three questions, each carrying a different weighting; the CCI is then computed as the average of the result of the three questions. The CCI is expressed as a net balance, therefore revealing changes in consumer expectations. The net balance is derived as the difference between the percentage of respondents expecting an improvement, and those expecting a decline.

Global Mood Time Series (GMTS) – The Global Mood Time Series is provided by Wall Street Birds, a service that analyses Twitter posts to assess the global 'mood' of an economy. Wall Street Birds uses a mood assessment tool that assigns a weighting according to positive and negative tone.

Google Search Volume Index (SVI) – Google Trends provides data on the frequency with which various search terms are searched for. The SVI is compiled using users' searches and hence SVI data can be extracted for specific words, shares, events and so on.

Gross National Happiness Index (GNHI) – The Gross National Happiness index is compiled from Facebook by determining the textual analysis of content from status updates. GNHI is calculated using the word-count methodology in which Facebook measures a status update's positivity (negativity) according to the relative frequency with which positive (negative) emotion words are used.

Investor Intelligence (II) – The Investor Intelligence survey reflects the sentiment of financial newsletter writers, with the sentiment of the writers being classified as bullish, bearish or neutral.

Michigan Consumer Sentiment Index (MSCI) – A survey-based sentiment index compiled by the University of Michigan; this index is a weighted average of responses to five survey questions about respondents' views on current and future financial conditions.

Raging Bull (RB) – An online financial community that allows users to post and read messages, own a private board, follow company data and participate in discussions.

Seeking Alpha (SA) – A personal finance social media website that serves as a platform for investors to provide insight and analysis garnered from their own personal experiences.

Yahoo! Finance (YF) – An online platform that offers the latest financial and business news with a focus on US markets.

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ABSTRACT

Traditional finance theory surrounding the risk-return relationship is underpinned by the CAPM which posits that a single risk factor, specifically market risk, is priced into asset returns. Even though it is a popular asset pricing model, the CAPM has been widely criticised due to its unrealistic assumptions and the APT was developed to address the CAPM's weaknesses. The APT framework allows for a multitude of risk factors to be priced into asset returns; implying that it can be used to model returns using either macroeconomic or microeconomic factors. As such, the APT allows for non-traditional factors, such as investor sentiment, to be included. A macroeconomic APT framework was developed for nine countries using the variables outlined by Chen, Roll, and Ross (1986) and investor sentiment was measured by the FEARS index (Da, Engelberg, & Gao, 2015). Regression testing was used to determine whether FEARS is a statistically significant explanatory variable in the APT model for each country. The results show that investor sentiment is a statistically significant explanatory variable for market returns in five out of the nine countries examined. These results add to the existing APT literature as they show that investor sentiment has a significant explanatory role in explaining asset prices and their associated returns. The international nature of this study allows it to be extended by considering the role that volatility spill-over or the contagion effect would have on each model.

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1 Introduction

Asset pricing can be broadly defined as a collection of theories whose aim is to determine the fair price of an asset. Moreover, there is a close relationship between the fundamental value of an asset and the appropriate return that asset should earn (which is determined by its price). As such, the collection of asset pricing theories is responsible for determining not only the fair price of an asset, but also its associated appropriate return (Krause, 2001). It is important to note that the fundamental value of an asset is often different to the observed price in the market. The fundamental value of an asset refers to the natural price such that it gives the owner a sufficient profit. On the other hand, the market price is determined by demand and supply and hence can deviate from the fundamental value; this deviation is short lived as the asset price will often return to its fundamental value in the long run (Smith, 1776).

Traditionally, many theories are focused on the fundamental value of an asset; asset pricing theories, however, are widely used to explain observed or market prices. These theories can cover a whole host of assets, such as bonds, stocks, interest rates, exchange rates, and derivatives of those underlying assets. Furthermore, the understanding of asset prices and returns is fundamental to an economy as it affects asset allocation, the allocation of resources, the measurement and management of financial risks, and influences individuals' decision making on a daily basis (Munk, 2013). Given the role asset pricing plays in the economy, it is critical that a thorough understanding of asset price behaviour is gained.

Traditional finance theory surrounding the risk-return relationship is underpinned by the Capital Asset Pricing Model (CAPM) – developed collaboratively by Markowitz (1952), Sharpe (1964), and Lintner (1965) – which posits that one risk factor, specifically market risk, is priced into asset returns. The CAPM is widely criticised for its unrealistic assumptions and its weakness in empirical testing; the Arbitrage Pricing Model (APT) – developed by Ross (1976) – was developed to address the CAPM's weaknesses. The most significant difference between the two models is that the APT allows for a multitude of risk factors to be priced into asset returns. This implies that the APT framework can be used to model returns using either macroeconomic or microeconomic factors. Research pertaining to the former was pioneered by Chen, Roll and Ross (1986) who found that industrial production, and changes in both the risk premium and yield curve exhibited the strongest explanatory power for expected stock returns. On the microeconomic side, Fama and French (1993) found that the book-to-market ratio and the size, as measured by market capitalisation, of portfolios have significant explanatory power for expected returns.

As mentioned, the APT framework allows for the modelling of expected returns using various factors – this is advantageous as it allows for a multitude of different approaches to be taken. One of these can be provided by behavioural finance which has emerged as a key research area in the finance world, fuelled by the shortcomings of traditional finance theory. The study of psychology and sociology in conjunction with traditional finance ensures a more holistic understanding of both the investor as well as financial market dynamics. Investor sentiment which encompasses individuals' emotions and how these impact decision making, is one principle of behavioural finance that can be applied to traditional finance.

The measurement of investor sentiment has evolved substantially – the fundamental measurement tool being survey data. Measurement was then extended to include proxies in the form of various market variables – the most notable of these being the Baker and Wurgler (2006) investor sentiment index which was constructed using six market-specific variables. Most recently, however, technology has enabled us to use various forms of media data to measure investor sentiment. An innovative investor sentiment index is the Financial and Economic Attitudes Revealed by Search (FEARS) index developed by Da, Engleberg and Gao (2015). The approach employed in the FEARS index involves using search volume data for a particular set of search terms from Google Trends. The search words used to construct the FEARS index encompassed both 'positive' and 'negative' words that were economic and financial in nature. This was done despite literature demonstrating that, in the English language, negative words are more useful in identifying sentiment (Tetlock, 2007). The nature of the data allows for a large degree of flexibility in what can be measured as a change in the set of search words can change what the index measures.

In their analysis, Da, Engelberg and Gao (2015) use a different set of words to construct both a microeconomic and macroeconomic FEARS index. Both indices were tested against: asset returns, a US volatility index (VIX) and daily mutual fund flows. When conducting their analysis the microeconomic FEARS index was found to have no statistically significant contemporaneous relationship with asset returns. The macroeconomic FEARS index, on the other hand, was found to have a strong and statistically significant contemporaneous relationship with asset returns. Specifically, increases in the macroeconomic FEARS index correspond with low market returns on the same day, but also predict high returns over the next few days. Increases in the macroeconomic FEARS index also predicted a negative change in the VIX a few days later. Finally, when tested against daily mutual fund flows, it was found that increases in the macroeconomic FEARS index triggered investors to sell equity funds, but not bond funds, thus pushing down the price of equity funds. This evidence indicates that measuring investor sentiment using macroeconomic variables better captures the variation in asset returns, volatility and mutual fund flows. This is likely due to the nature of data as it is more aligned to what individuals are searching for on Google.

The scope of this study is to replicate the FEARS index (Da, Engelberg, & Gao, 2015) using search volumes for macroeconomic key words from Google Trends for a variety of countries. Thereafter, this index will be used as an input variable into a macroeconomic APT model. Regression testing will be conducted both with and without the FEARS variable. The outcome will give an indication of whether the FEARS index is an appropriate risk factor with the ability to explain returns. It is important to note that this implies that the objective of the study is the feasibility of APT factors in explaining market returns, and not the creation of an APT model. The choice to focus on macroeconomic variables is driven by the following:

1. Macroeconomics is the study of an economy as a whole as well as the variables that control that economy. As such, on a high level they would describe the drivers of a country's economy as well as its stock market. A macroeconomic approach coupled with the international nature of this study implies that a level of comparison would be possible as to the drivers of the different economies – this would provide much richer insight into these countries than focusing on microeconomic factors which are subject to large amounts of noise from the individual countries.
2. Hence, the macroeconomic APT model of Chen, Roll, and Ross (1986) was chosen as the base for this study; it makes use of macroeconomic variables which have been shown to capture the variation in market returns.
3. The evidence uncovered by Da, Engelberg and Gao (2015) indicated that their macroeconomic FEARS index outperformed the microeconomic alternative. This implies that macroeconomic household sentiment was able to explain returns better than their microeconomic sentiment index.
4. The lowest frequency available for many macroeconomic metrics is monthly. Google Trends data, on the other hand, is available on both a monthly and weekly basis. This will provide insight into how quickly Google Trends data is reflected in stock prices as well as what information is captured in a trends variable.

5. Finally, when describing an asset pricing model to explain market returns it is important that there is consistency as to the nature of the variables – a macroeconomic base model should be accompanied by a macroeconomic sentiment variable. This consistency in approach implies that insights can be drawn about a specific topic – in this case, the macroeconomic drivers of a country's stock market and whether investor sentiment plays a role in explaining the variation in returns as well.

The empirical analysis will include South Africa, the remaining BRICS countries (Brazil, Russia, India and China) as well as a number of developed markets from the G7[1]. The primary reason for pursuing this study on an international scale is that it will allow for comparisons across both developed and developing markets. Specifically, existing literature documents the vastly different characteristics of developing markets which include: higher expected asset returns, low correlations with developed markets, more predictable returns and higher volatility (Bekaert & Harvey, 1997). As such, understanding the differences between developed and developing markets as well as the drivers behind them will add further insight.

It is important to highlight that the approach employed in this study is not to create the International APT (IAPT) of Solnik (1974) – this will be discussed in more detail in Section 2.2.1. The IAPT involves using global macroeconomic factors to explain the variation in global stock returns – this approach does not necessarily allow for the level of insight and comparability desired in this study as comparing an IAPT for BRICS and various G7 countries would give little insight into the individual countries themselves. Moreover, the empirical testing of the IAPT is ambiguous as it tests a joint hypothesis that the IAPT holds and that global markets are integrated. As such, one would be unable to distinguish whether empirical results indicate that the IAPT holds or if international markets are segmented. For these reasons, the IAPT will be covered from a literature perspective but will not be empirically tested.

This study yields insight into two different aspects of literature. Firstly, it builds upon existing APT literature as it considers the role a behavioural finance factor, such as investor sentiment, could have in explaining asset prices and their associated returns. Furthermore, the

[1] The G7 is a group consisting of seven major economies, as identified by the International Monetary Fund, which regularly meet to discuss economic issues.

international nature of this study yields insight into the economies and stock markets of the various counties under examination.

1.1 Issues and Problems to be Investigated

The aim of many traditional finance models and theories has been to gain a better understanding of financial markets; specifically, which factors could be the drivers behind asset returns and which ones could be used to predict returns in the hopes of making superior returns. As much as these models provided valuable insight into financial markets, they were limited by their foundational assumptions which are largely unrealistic. As a result, academics sought alternative explanations for events in financial markets; one of which was to investigate the role that individuals' emotions play in these markets.

Behavioural finance has provided an exciting avenue of research into explaining financial markets and has been successful in explaining phenomena in the market that were previously unable to be explained under traditional finance models and theories. One aspect of behavioural finance which has received a lot of attention in its ability to explain stock returns is investor sentiment; this encompasses individuals' emotions and how these impact decision making. Given the existing literature regarding investor sentiment and its ability to explain returns as well as the need to better understand the complexity of financial markets, the natural question is then whether financial market returns can be better explained by incorporating an investor sentiment factor into a return generating process (such as the APT).

The problem facing many existing and traditional asset pricing models is that they are grounded in an assumption of a completely rational investor. Asset pricing models do not take into account the effect an irrational investor could have on explaining market returns. This is precisely what this study will consider. Considering investor sentiment, measured by the FEARS index, as a factor in an APT model will provide great insight into the effect that investors' thoughts and beliefs may have on determining market returns. As such, the objective of this research is to determine whether investor sentiment has explanatory power for market returns in various countries around the world. More generally, the objective is the feasibility of various APT factors, including investor sentiment, in explaining market returns and not the creation of an APT model.

A potential problem or limitation in pursuing research of this nature is the risk that investor sentiment could already be incorporated into any one of the factors in the return generating process. Hence, incorporating an investor sentiment factor into the APT would prove fruitless as its effects would already be captured elsewhere. That being said, regression testing will be conducted both excluding and including the FEARS variable; thereafter, it will be determined which model is superior in explaining returns. This could reveal that the macroeconomic model without FEARS could be superior which could imply that investor sentiment does not play an explanatory role or that investor sentiment is captured elsewhere in one of the explanatory variables. Additionally, robustness checks will be conducted on the FEARS indices for the various countries to determine if any statistical relationship found between FEARS and market returns is a true statistical relationship or is in fact driven by noise traders.

1.2 Feasibility of Study

This study seeks to determine if investor sentiment is a suitable risk factor to be included in an APT model to explain stock returns. As demonstrated in the literature review, an APT model is quite dynamic in that it allows for a number of factors to model returns, with a large body of research investigating the suitability of various factors. The literature has also shown the effect that investor sentiment has on financial markets; with investor sentiment able to be measured using a number of different methodolgies. A study including an investor sentiment measure into the APT has not been attempted in South Africa, and has had limited coverage on the international scale. Therefore, this study will add to the existing literature about the role investor sentiment plays in asset pricing as well as determine the viability of investor sentiment as an explanatory variable in a macroeconomic APT framework. Given that much of the existing literature on asset pricing theory and investor sentiment has been conducted internationally and mainly in developed countries, the nuances of examining various developing markets including South Africa, will add an interesting dimension to the study.

1.3 Research Objective and Hypothesis

1.3.1 Primary

Determine if an investor sentiment indicator, the FEARS index, is a statistically significant factor in explaining returns using the APT model.

As such, the primary hypothesis is as follows:

H_0: Investor sentiment is not a statistically significant factor in the APT

H_A: Investor sentiment is a statistically significant factor in the APT

This validity of this hypothesis will be assessed according to the number of countries where FEARS was found to be statistically significant. If investor sentiment is found to be statistically significant in more than 50% of the countries tested, then the hypothesis can be declared valid. Despite the fact that the primary hypothesis is about the APT in general, the validity of the hypothesis will be determined by the data being used.

1.3.2 Secondary

Determine if investor sentiment is statistically significant in explaining market returns for various countries around the world.

As such, the secondary hypothesis applicable to each country under examination is as follows:

H_0: Investor sentiment is not a statistically significant explanatory variable for explaining market returns in each country

H_A: Investor sentiment is a statistically significant explanatory variable for explaining market returns in each country

1.4 Summary of Results

The aim of this study is to determine if investor sentiment, as measured by the FEARS index, plays a statistically significant role in explaining market returns in various developed and developing nations around the world. The FEARS index is constructed using Google Trends search volume data and is then incorporated into a macroeconomic APT model. Regression analysis will determine if investor sentiment is in fact an explanatory factor in an APT framework.

The results of the analysis can be explained in two parts. First, the results showed that different macroeconomic variables explained returns in different countries. The variables which had explanatory power in multiple countries include the real interest rate, risk premium, and term structure of rates. Variables such as inflation and industrial production had explanatory power, albeit in few countries. When the FEARS index was included as an explanatory variable the explanatory power of each country's model improved, some with a greater magnitude than others. FEARS was found to have statistically significant explanatory power in five out of the nine countries examined. Specifically, investor sentiment can be used as a factor to explain market returns in Russia, SA, Japan, UK, and the US. Unfortunately, investor sentiment lacked explanatory power in the remaining countries: Brazil, India, China, and Germany. These results address both the problem as well as the objective outlined in Section 1.1. The incorporation of the FEARS index, a macroeconomic investor sentiment measure, into an APT model addressed this problem. Furthermore, the results of the statistical testing meet the objective of determining whether investor sentiment has explanatory power for market returns in various countries around the world. Finally, no clear link could be established between investor sentiment's explanatory powers in developed versus developing nations.

These results provide insight into the countries under examination and can be used by both traders and policy decision makers to inform better decisions. Specifically, those macroeconomic variables found to explain the variation in market returns as well as the role that investor sentiment plays in certain economies can be exploited by traders to maximise their profits. On a high level, the regression results can be used by policy decision makers to ensure that policies are made in the best interests of the country as well as to address some of the factors which could make the country more susceptible to the effects of investor sentiment.

1.5 Chapter Outline

The following chapters will be presented in this dissertation.

Chapter Two provides the literature review for this study; it includes an overview of popular asset pricing models and their extensions, as well as a history and overview of investor sentiment, the various methods in which it is measured and the role it plays in explaining financial returns and other financial theories and phenomena.

Chapter Three outlines the data used for this study as well as the methodology applied in the study. Specifically, it details the choice of countries, APT factors, and the creation of the FEARS index as well as the statistical testing conducted to meet the objectives of this study.

Chapter Four presents the results uncovered in this study by each country under examination; it also includes a discussion of the results per country as well as on an overall level.

Finally, Chapter Five presents the concluding remarks of this dissertation as well as avenues for further research.

2 Literature Review

Fundamentally, this study focuses on asset pricing and how investor sentiment can play a significant and explanatory role when pricing assets. The first two sections introduce the relevant asset pricing frameworks, specifically the CAPM and the APT. The development of the CAPM, its underlying assumptions, and modifications over time are discussed with the aim of demonstrating that the demise of the CAPM, although fundamental in understanding asset pricing, lies in its assumptions. The APT model is then introduced and discussed as a framework which allows for a variety of factors to be used in explaining asset prices and returns. Thereafter, behavioural finance and investor sentiment are introduced as further explanatory variables in the APT. Lastly, an important aspect when conducting textual analysis, as is employed in this study, is to consider the asymmetric effect between positive and negative news.

2.1 Asset Pricing Models

2.1.1 The Capital Asset Pricing Model

The Capital Asset Pricing Model (CAPM) is considered to be the basic theory that links risk and return. Through the collaborative efforts of Markowitz (1952), Sharpe (1964), and Lintner (1965), it has been developed and refined in an attempt to understand the trade-off between risk and return in financial decision making.

The theoretical background of the CAPM is underpinned by Sharpe's initial work on the risk-return relationship. His approach was based on the intuition that an investor chooses to create an efficient portfolio – one that maximises return for a given level of risk and minimises risk for a given level of return. Risk itself can be classified as either systematic or unsystematic. The latter component refers to the portion of risk that can be attributed to firm-specific events and thus can be eliminated through holding a diversified portfolio of assets. Systematic risk, however, refers to the risk inherent in a particular stock and hence cannot be eliminated through diversification. The fact that some risk can be diversified away is critical in capital market theory as it implies that any rational investor will eliminate the risk through diversification and hence it will become irrelevant. As a result, investors' primary concern will rest with the level of risk that remains despite diversification efforts, non-diversifiable or market risk. This further implies that the level of non-diversifiable risk is of primary importance in selecting assets. The CAPM is an important tool used to link this non-diversifiable risk and return for assets; it measures a stock's expected return based on its expected volatility in the market. Sharpe's proposition is that the expected return of any asset depends on the amount of risk it bears, as measured by its beta.

The formation of the CAPM also made use of the theory of portfolio choice, developed by Markowitz (1952) to understand how individuals allocate their assets under uncertainty. This theory outlined that an investor's portfolio choice can be reduced to balancing a trade-off between the expected return on the portfolio and its variance. Given that diversification allows for risk reduction of a given portfolio, as measured by its variance, portfolio risk will not only depend on the return and variance of each asset, but also on the pair-wise covariances of all assets in the portfolio. Under this theory the expected return of a portfolio is calculated as the sum of the weighted returns of the assets within the portfolio.

Sharpe (1964) then expanded on the foundation built by Markowitz (1952) by considering the implication of adding a risk-free asset. Due to its nature, a risk-free asset's returns have zero standard deviation and hence its returns will be uncorrelated with that of a risky asset. The risk-free asset is simply viewed as compensation for the time value of money. The introduction of a risk-free asset into the portfolio choice selection implies that investors are now faced with the decision to either choose an optimum risky portfolio or allocate their funds between the risky portfolio and risk-free asset. Regardless of their decision, there will be implications on portfolio risk and return. As before, the expected return on the portfolio is calculated as the weighted sum of the individual assets that make up the portfolio – an adaptation to the initial equation is simply made to include the risk-free component.

Put simply, the CAPM states that an asset's risk premium is directly proportional to both the beta and risk premium of the market portfolio.

$$E(R_P) = R_{rf} + \beta_m[E(R_m) - R_{rf}] \quad \textbf{(1)}$$

Where $E(R_P)$ is the expected return on the portfolio, R_{rf} is the risk free-rate, $E(R_m)$ is the return on the market portfolio.

The formulation and application of the CAPM is underpinned by a number of assumptions:

- Investors seek mean-variance efficient portfolios – investors seek low volatility and high returns.

- Markets are perfect and thus taxes, inflation, transaction costs and short-selling restrictions are not taken into account.
- All investors have homogeneous expectation about returns, volatilities and correlations of securities. This implies that investors estimate identical probability distributions
- All assets are infinitely divisible and perfectly liquid.
- Investors can lend and borrow an unlimited amount of money at the risk-free rate
- All investors plan for one identical period.
- Capital markets are in equilibrium – all assets are priced properly in line with their risk level.

It is clear that the assumptions of the CAPM are unrealistic and they have become a huge source of weakness and criticism of the model. Moreover, empirical evidence has shown that relaxing the assumptions only has a minor effect on the model and would not change its implications or conclusions (Black, 1972; Reilly & Brown, 2003). Another source of the CAPM's weakness stems from empirical testing; in many cases the CAPM has demonstrated poor explanatory power in overestimating the risk-free rate and underestimating the market risk premium. Finally, beta which is the measure of market risk does not remain stable over time and hence beta can only be estimated based on historical data (Free, 2010). Given these points, the practicality and predictive power of the CAPM model is compromised.

The criticisms against the CAPM have resulted in a number of extensions being made to the CAPM in the hopes of improving its explanatory power and overcoming its empirical weaknesses. The most notable of these extensions are listed below and will be discussed in further detail:

- The International CAPM (ICAPM), first introduced by Solnik (1974), which uses the same inputs as the CAPM but also takes into account other variables that influence returns on assets on a global basis.
- The Fama and French Three-Factor Model (1993) which incorporates size and value factors in addition to the market risk factor.
- The Carhart Four-Factor Model (1997) which expands upon the aforementioned Fama and French Three-Factor Model (1993) by including a momentum factor.
- The Fama and French Five-Factor Model (2014) which builds upon the Three-Factor model by including profitability and investment factors.

2.1.1.1 International CAPM

The United States was the country of focus when the CAPM was developed and hence provided insight into that specific market. Although the CAPM has been empirically tested in various other countries around the world, it failed to account for an important phenomenon around the world: globalisation. The advent of technology enabled globalisation and forced individuals to consider not only their domestic market for investment purposes, but also foreign markets. Thus it became necessary to understand how global factors may affect asset returns as investors were now participating in multiple stock markets. This became a further source of criticism of the original CAPM as it only accounted for factors in a single country with no insight into global markets. The ICAPM, originally outlined by Bruno Solnik in 1974, was able to evaluate investment portfolios with different currency bases as it factored in global variables that may influence asset returns (Naderi, Amirhhoseni, & Ahmadinia, 2012).

Mathematically, the ICAPM is outlined as follows:

$$E(R_i) = R_{fi} + \beta_i[E(R_{WM}) - R_{fw}] \quad \textbf{(2)}$$

Where R_{fi} is the risk free rate in the country of security i, R_{WM} is the return on the worldwide market portfolio, R_{fw} is the worldwide risk-free rate and β_i is the international systematic risk of security i.

Equation (2) above is the first iteration of the ICAPM and was naturally a single factor model. Early research from Solnik (1974) and Sercu (1980) found that this method could not completely explain stock returns on a global scale (Naderi, Amirhhoseni, & Ahmadinia, 2012). It appears that even on an international stage more than one risk factor is needed in explaining asset returns (Perold, 2004). Thus it has been advocated that a multi-factor ICAPM would likely provide more insight in explaining asset returns.

2.1.2 Fama and French Three-Factor Model

As previously mentioned, the Fama and French Three-Factor Model (1993) explains the risk and return of shares by adding two variables to the original CAPM's market risk factor; namely, size measured by market capitalisation that takes into account the extra risk in small companies and value, which demonstrates the value in owning out-of-favour shares that have attractive valuations. This model is believed to be superior to the original CAPM as it not only reveals the primary factors that drive stock returns but also provides investors with a strategy for using those factors in their portfolios to secure a higher expected long-term return.

Mathematically, the Three-Factor Model is outlined as follows:

$$E(R_P) = R_{rf} + \beta_m\left[E(R_m) - R_{rf}\right] + \beta_{SMB}(SMB) + \beta_{HML}(HML) \quad \textbf{(3)}$$

Where $E(R_P)$ is the expected return on the portfolio, R_{rf} is the risk-free rate, $E(R_m)$ is the return on the market portfolio, SMB represents the size factor (small cap shares minus big cap shares) and HML represents the value factor (high book-to-market minus low book-to-market shares).

Empirically, under the single-factor CAPM, beta alone was able to capture 70% of a stock's actual return; however the combination of the three factors was found to capture 95% of a stock's actual returns. This model can be further applied in event studies of the stock price response to firm-specific information. In a single-factor model the residuals from a regression of the stock's return on a market return are used to isolate the firm-specific component of returns. Fama and French (1993) found that a three-factor regression which includes the *SMB* and *HML* variables will do a better job at isolating the firm-specific component of returns. This Three-Factor Model has been tested rather extensively with the same result: adding a size factor and a value factor greatly improves upon the explanatory power of the CAPM. Thus it can be inferred that more than one systematic risk factor is at work in determining asset prices (Perold, 2004).

2.1.3 Carhart Four-Factor Model

Momentum is a phenomenon first uncovered by Jegadeesh and Titman (1993) who documented that "strategies which buy stocks that have performed well in the past and sell stocks that have performed poorly in the past generate significant positive returns" (1993, p. 1). This was further attributed to the fact that investors underreact to the release of firm-specific information, which is a cognitive bias. Carhart (1997) posited that momentum could provide important insight into the expected return of a portfolio and hence built upon the Fama and French Three-Factor Model (1993) by including a momentum factor. Momentum was calculated by subtracting the cumulative historical performance of the highest performing firms from the cumulative historical performance of the lowest performing firms, lagged by one month. A stock was said to demonstrate momentum if its prior 12 month average was positive.

Mathematically, the Four-Factor Model is outlined as follows:

$$E(R_P) = R_{rf} + \beta_m\left[E(R_m) - R_{rf}\right] + \beta_{SMB}(SMB) + \beta_{HML}(HML) + \beta_{UMD}(UMD) \tag{4}$$

Where $E(R_P)$ is the expected return on the portfolio, R_{rf} is the risk-free rate, $E(R_m)$ is the return on the market portfolio, SMB represents the size factor (small cap shares minus big cap shares), HML represents the value factor (high book-to-market minus low book-to-market shares) and, UMD represents the momentum factor (the premium on winner minus losers).

In his empirical testing, Carhart (1997) identified three important rules of thumb for those investors seeking to maximise their wealth: 1) Avoid funds with persistently poor performance; 2) Funds with high returns last year have above average expected returns next year, but not in the years thereafter; and 3) The investment costs of expense ratios, transaction costs, and load fees all have a direct and negative impact on performance.

2.1.4 Fama and French Five-Factor Model

One of the factors in the Fama and French Three-Factor Model (1993) that provided significant explanatory power to the overall model was the value factor, measured by the book-to-market ratio. As corollary to their 1993 results, Fama and French considered if profitability and investment could add to the explanation of stock returns provided by the book-to-market ratio. As a result, Fama and French considered an augmented Three-Factor model which incorporates profitability and investment factors, thus making it a Five-Factor Model (2014).

Mathematically, the Five-Factor Model is outlined as follows:

$$E(R_P) = R_{rf} + \beta_m\left[E(R_m) - R_{rf}\right] + \beta_{SMB}(SMB) + \beta_{HML}(HML) + \beta_{RMW}(RMW) + \beta_{CMA}(CMA) \tag{5}$$

Where $E(R_P)$ is the expected return on the portfolio, R_{rf} is the risk-free rate, $E(R_m)$ is the return on the market portfolio, SMB represents the size factor (small cap shares minus big cap shares), HML represents the value factor (high book-to-market minus low book-to-market shares), RMW represents the profitability factor (the difference in returns on diversified portfolios of shares with robust and weak profitability) and CMA represents the investment factor (the different in returns on diversified portfolios of low and high investment shares).

The empirical outcome of this model was not as favourable as the Three-Factor Model as the Five-Factor Model failed to capture and explain the variation in returns. The authors, however, did estimate that the model could explain between 69% and 93% of the cross-sectional variation in returns (Fama & French, 2014). It would appear that there is a fine balancing act when it comes to multi-factor asset pricing models as one must balance the number of factors which could explain returns, the choice of these factors and the interaction of these factors with one another which might give spurious results. Three and four factor models appear to fare well in empirical testing and capture a large part of the cross-sectional variation in returns, however the five factor model, although still in infancy, did not perform well in empirical testing. As there is no right or wrong when it comes to choice of factors, the possible reason for this outcome could be the interaction of the chosen factors with each other.

2.1.5 Summary

The cornerstone of asset pricing can be found in the CAPM which asserts that the return on any given asset is a function of market risk. The CAPM, much like any other model, is based on a set of assumptions; in the case of the CAPM, however, these assumptions are quite restrictive and unrealistic which makes the CAPM weak in empirical testing. Various attempts have been made to address the pitfalls of the CAPM; many of these involved augmenting the original model to include various other risk factors. The most notable of these augmentations include the International CAPM, as well as a three-, four-, and five-factor models. Empirically, however, the ICAPM struggled in explaining global returns and it is possible that a multi-factor ICAPM could be more suitable. With respect to the other models, the three- and four-factor models were found to be empirically strong, whereas the five-factor was not as successful in explaining the variation in returns. This could possibly be caused by the interaction amongst factors.

2.2 Arbitrage Pricing Theory

The Arbitrage Pricing Theory (APT), originally developed by Ross (1976) is an asset pricing model that explains cross-sectional variation in returns. Similar to the CAPM, the APT begins with an assumption on the return generating process: each asset return is linearly related to several common factors plus its own idiosyncratic disturbance. The APT posits that the expected return on any financial asset can be explained by two factors: macroeconomic or security-specific influences and the asset's sensitivity to those influences; this has the advantage of allowing the user to adapt the model to the particular asset being analysed.

The APT, as with any model, is based on a number of assumptions:

- The theory is based on the assumption of capital market efficiency and hence assumes that all investors will trade with the intent of profit maximisation.
- Moreover, it assumes that each investor will hold a unique portfolio with its own array of betas, as opposed to the identical and immeasurable market portfolio assumed under the CAPM.
- It assumes that no arbitrage exists and if it were to occur the market participants will engage to benefit out of it and bring the market back to equilibrium levels.
- It assumes markets are frictionless – there are no transaction costs, no taxes, short selling is possible and there are an infinite number of securities available.

Assumptions are necessary in the development of any theoretical model; however, the assumptions of the APT are far less restrictive than those of the CAPM. Thus far, it may seem that the APT model is a superior one to the CAPM for a number of reasons, however the nature of the model, which makes it more customisable, also makes it more difficult to apply because determining the appropriate factors takes a tremendous amount of research. Not only is it practically impossible to detect every factor that may have an impact on the return of a security, but there is absolutely no indication of how many factors would be sufficient to make the model robust. Much of the empirical research has shown that one comes close to a robust model with between four and five factors (Roll & Ross, 1980).

The APT (Ross, 1976) in its barest form describes that for any asset, i, its expected return is described as follows:

$$E_i = \rho + \beta_i(E_m - \rho) \qquad \textbf{(6)}$$

Where ρ is the risk-free rate of return and $\beta_i = \frac{\sigma_{im}^2}{\sigma_m^2}$ is the beta coefficient on the market, where σ_m^2 is the variance of the market portfolio and σ_{im}^2 is the covariance between the returns on the i^{th} asset and the market portfolio

All asset pricing models are assumed to estimate a pricing kernel and hence describe the data generating process of returns. The APT, however, can be viewed as a framework where various factors can be used to explain asset prices and their associated returns. As such, the more general APT allows for n return generating factors; hence the expected return for any asset, i, can be described as follows:

$$E_i = \rho + \beta_1 RP_1 + \beta_2 RP_2 + \beta_3 RP_3 + \ldots + \beta_n RP_n \qquad \textbf{(7)}$$

Where ρ is the risk free rate of return and β_n is the sensitivity of the asset's returns to that specific factor and RP_n is the risk premium associated with the particular factor.

One distinct difference between the CAPM and APT models is that (6) and (7) hold in both equilibrium and disequilibrium situations. Another stark difference compared to the CAPM is that no particular portfolio plays an important role in the APT; specifically, the market portfolio plays no special role in the APT whereas it is the crux of the CAPM. The APT is also not restricted to a single period, as the CAPM is, as the APT will hold in both single and multi-period scenarios (Roll & Ross, 1980).

There are, however, some weak points in the assumptions and arguments Ross (1976) has made around the number of assets and the application of the law of large numbers. As the number of assets increases, wealth will also increase. As a result, the levels of risk aversion in some economic agents may change. The application of the law of large numbers implies that any noise[2] becomes negligible for a larger number of assets; however, if the degree of risk aversion

[2] Noise refers to trading which takes place using data other than fundamental data (De Long, Shleifer, Summers, & Waldmann, 1990).

increases as the number of assets increases then noise might no longer be negligible and in fact have a persistent influence on pricing (Ross, 1976). It is rare to find a model that is perfect, however having a number of options to consider in terms of asset pricing models can only be viewed in a positive light.

Empirical testing of the APT centres on the choice and number of factors that should be included in the model. The latter component was examined by Roll and Ross (1980), who replicated and extended work done by Gehr (1975). Roll and Ross (1980) employed a data set spanning across the period 1962 to 1972. Returns for 1 260 securities were obtained, collected from both the NYSE and AMEX; these securities were also split in 42 groups of 30 each for the purpose of sub-period analysis.

The results indicate that three factors are present in expected returns of equities traded on the NYSE and AMEX; the evidence of a fourth was present but less conclusive. Although these results are reassuring for the APT, the possibility does remain that other variables are also "priced" even though they are not related to non-diversifiable risk. In this particular APT model, these variables should not be able to explain expected returns and hence if some variables were found to have explanatory power, then this model of the APT would be rejected. Roll and Ross (1980) examined one variable in particular, the total variance of individual returns or "own" variance. Testing revealed that this variable does indeed have significant explanatory power which suggests that this particular APT might be false. Upon further analysis, it was found that the individual returns were found to be highly skewed. Skewness in data can create dependence between the sample mean and sample standard deviation and hence could explain the sample mean's dependence on "own" variance. It would be unreasonable to reject this APT model based on these results but should always be a consideration when testing the empirical robustness of the APT. It is important to highlight that variance captures noise or exogenous variables and sentiment could very well be one of these variables. Thus, by adding a sentiment factor to the APT model it could eliminate a portion of this variance thereby improving the explanatory power of the APT. Nonetheless, the overarching conclusion of the research conducted by Roll and Ross (1980) was positive in that the APT performed well under empirical scrutiny and is considered a reasonable model for explaining the cross-sectional variation in average asset returns.

Chen, Roll and Ross (1986) conducted research as to whether macroeconomic variables are risks that are rewarded in financial markets. This research is consistent with the APT (Ross,

1976) which dictates that asset prices should depend on their exposure to state variables that describe the economy. Their sample period covered 371 months from January 1953 to November 1983, with the following variables being included: 1) inflation (expected and unexpected), 2) the Treasury bill rate, 3) the return on long-term government bonds, 4) industrial production, 5) the return on low grade bonds, 6) the return on an equally-weighted index, 7) the return on a value-weighted index, 8) consumption and 9) the oil price.

Individual stock returns were modelled according to a factor model as outlined below:

$$R = a + \beta_{MP}MP + \beta_{DEI}DEI + \beta_{UI}UI + \beta_{URP}URP + \beta_{UTS}UTS + \varepsilon \quad \textbf{(8)}$$

Where MP is the monthly growth in industrial production, DEI is the change in expected inflation, UI is unexpected inflation, URP is the risk premium and UTS is the term structure; the betas are the loadings on the state economic variables, a is the constant tem and ε is an idiosyncratic error term.

Their results were consistent with efficient market theory as well as rational expectations in asset pricing theory – asset prices were found to be dependent on their exposures to the state variables that describe an economy. Industrial production, changes in the risk premium, and changes in the term structure of rates were found to be statistically significant in explaining market returns. Weaker evidence was found for the explanatory power of both expected and unexpected inflation, albeit only during periods of high volatility. Overall, when stock returns are exposed to economic news, they are priced in accordance with their exposures. Moreover, economic news can be captured through innovations in state variables whose identification is grounded in simple and intuitive economic and financial theory.

A British perspective is offered by Beenstock and Chan (1986) who conduct empirical analysis on both the viability of the APT and the CAPM as asset pricing models in the UK. During the time period from December 1961 to December 1981, data pertaining to 220 British shares was collected. It appears that in the UK the APT has the ability to explain a high proportion of the variance of estimated expected returns; this result is broadly similar to that which was obtained by investigators of the US market. Moreover, the explanatory power of a 20 factor APT model was found to be significantly greater than that of a 4 factor model, this indicates a relatively complex financial market as a large number of risk factors will be priced into the UK market. An important caveat is that this result should be viewed more as indicative as there is a large amount of ambiguity surrounding tests of the APT and the authors could not sure that none of these factors are idiosyncratic. The last piece of empirical analysis pertaining to the single factor CAPM model yielded disappointing results as the CAPM was always rejected in favour of the APT. As a whole, the results indicate that the APT was a stronger asset pricing model in the UK and that the APT captures the complexity of the market through multiple factors.

Much of the existing literature pertaining to the APT tests whether it has the ability to model expected returns using a number of risk factors. It would then be logical to wonder whether the APT could be used to model the value of other financial instruments. For example, in an option the underlying asset is the sole risk factor and hence in theory the APT could be used to derive an option-pricing formula as an alternative to the seminal Black-Scholes formula. An option-pricing framework was developed by Chang and Shanker (1987); however the framework was kept largely general because it includes existing option-pricing formulas as special cases. Within this framework, the authors were able to derive a new and simple option-pricing formula by assuming that securities' return distributions are truncated normal – this refers to the probability distribution of a normally distributed random variable whose value is either bounded below or above (or both) (Burkardt, 2014). Preliminary tests of this new formula suggest that it is simple to apply and performs as well as the Black-Scholes formula. The application of the APT to option pricing once again highlights the fluid and dynamic nature of the APT model compared to the rigidity of the CAPM.

The aforementioned study by Chen, Roll and Ross (1986) was based in the United States and hence provided great insight into that specific market; however, establishing the APT's international robustness would assist in determining whether this model is suitable for use in various markets. Hamao (1988) addressed this gap by providing a Japanese perspective, thus providing a comparison to the initial work done in the US. At the time, the Japanese capital market was second in size only to the US Equities market value of $500 billion and an average daily trading volume of 300 million shares. One interesting similarity in these capital markets is that there are two sections to the Tokyo Stock Exchange, much like the dominance of the New York and American Stock Exchanges in the US. Following World War II, Japan developed an active equity market but did not develop an active bond market. Investors were dissuaded from entering the market due to government-imposed interest rate ceilings that were intended to stimulate investment. Corporations tended to rely on bank loans instead of bond issues and hence the bond market remained undeveloped. Moreover, no long-term government bonds were issued because a balanced budget was strictly sustained to prevent the occurrence of post-war hyperinflation. The first long-term government bond was issued in 1966 and massive offerings only began in 1975. The idiosyncrasies of the Japanese capital market add an interesting lens to this robustness study; however, they also present some difficulties with respect to the availability of data. There is a lack of macroeconomic data that exactly parallels the US series; specifically, in order to know the slope of the yield curve and the risk premium, one needs data from an active bond market. The secondary bond market did not exist before 1975 and hence the time frame and sample of this study is somewhat limited. Hamao (1988) employed the same variables as Chen, Roll and Ross (1986); specifically, industrial production, inflation, risk premia, the term structure, foreign exchange, market indices and oil prices. The results indicated that changes in expected inflation, unanticipated changes in risk premium and unanticipated changes in the slope of the term structure have a significant effect on the Japanese stock market. Changes in monthly production and changes in terms of trade were also found to have an effect; however the evidence was weaker in these instances. It was found that unanticipated changes in foreign exchange, value- and equally-weighted market indices neither have statistically significant risk premia nor do they capture systematic risk missed by other macroeconomic variables. Similar to the finding by Chen, Roll and Ross (1986), oil price changes were not factored into the Japanese stock market. These results are largely consistent with those uncovered in the US which is promising despite the study suffering from a short observation period and some data issues. It would appear that in this instance the APT was found to be robust on an international stage.

An investigation into whether the APT or CAPM is a better indication of risk in the Indian stock market was conducted by Dhankar and Singh (2005). This study uses the closing prices of frequently traded shares of large and medium size companies listed on the BSE200, Nifty and Junior Nifty over a 12 year period from January 1991 to December 2002. The initial step involved using principal component analysis to approximate a factor structure. Thereafter, using monthly and weekly returns, the authors determined which model would be a better indication of asset risk in India. The evidence suggests that an APT model may lead to better estimates of expected returns than the CAPM as APT models explain the return generation and forecasts return much better than the CAPM. Moreover, when it came to checking if factors were priced and which model explained a larger percentage of variance the APT performed much better. Despite the idiosyncrasies of the Indian market, the final recommendation provided by the authors was that decision makers should give due consideration to multi-factor models like APT and not rely solely on single-factor models like the CAPM. Industrial production, changes in the risk premium and changes in the yield curve were found to have the strong explanatory power in explaining expected stock returns. Unanticipated inflation and changes in expected inflation were also found to be significant, however exhibited a somewhat weaker relationship. A striking result from this research was that although the value-weighted NYSE explained a significant portion of the time-series variability in stock returns, it has an insignificant influence on expected returns when compared against the economic variables. Moreover, innovations in oil prices are not significantly related to asset pricing.

2.2.1 International Arbitrage Pricing Theory

The APT has largely been tested as a domestic asset pricing model; however the need for an international equivalent was identified.

Solnik (1974) was one of the first to present an equilibrium model of the international capital market, by using the CAPM as the asset pricing model. The empirical tests were largely inconclusive based on the fact that the world market portfolio is un-identifiable (Roll, 1977). The second problem centred on disaggregating the assets of national investors using a number of different currencies.

An attempt to extend the APT of Ross (1976) into the international area was made by Solnik (1983) who was able to overcome some of the difficulties mentioned above and developed the International APT (IAPT). The testability of the APT was hypothesised to be more robust than previous international asset pricing models as unlike asset returns, factors do not have to be translated from one currency to another.

Empirical testing of Solnik's (1983) model was conducted by Cho, Eun and Sebert (1986) who sought to test the joint hypothesis of international capital markets being integrated and the APT being valid internationally. The approach to estimate the systematic risks – that is the factor loadings for each asset – and the cross-sectional analysis to test the pricing implications of the IAPT were carried out in a methodology similar to Roll and Ross (1980). The result of this showed that there are three or four worldwide common factors, similar to the outcome reached by Roll and Ross (1980). The cross-sectional results led to the joint hypothesis being rejected implying that international capital markets are in fact segmented and that the APT might not hold up in an international setting. Unfortunately, due to the testing of a joint hypothesis, it remains unclear as to whether these results reflect that international markets are segmented or that the IAPT has failed.

Further empirical analysis on the IAPT was conducted by Abeysekera and Mahajan (1990) who sought to test the same two hypotheses outlined by Cho, Eun and Sebert (1986) – that is whether certain risk factors are priced in international capital markets which can be tested jointly with the hypothesis that international capital markets are integrated. The countries under investigation by Abeysekera and Mahajan (1990) are the three most developed nations in the world; namely, the US, UK and Canada. The basic data used in this study are the monthly returns on individual shares, the spot exchange rates and the Treasury bill rates in the three countries; the sample period of this study spanned 168 months in total, from January 1973 to December 1986. The results uncovered very weak evidence to support the IAPT as a valid international capital asset pricing model and that the number of factors in a given economy is invariant to the currency in which the returns are denominated. Overall, the results do not lend support to the IAPT as an international capital asset pricing model which is largely consistent with the conclusions reached by Cho, Eun and Sebert (1986).

The aim of this study is not to create an IAPT for a group of countries, for example the BRICS or G7 nations, but instead to create country-specific APT models for each of the countries chosen. There are two reasons for adopting this approach:

1. Constructing an IAPT for a group of countries would not allow for the level of insight desired in this study – comparing an IAPT for BRICS and G7 countries would reveal very little about the individual countries themselves.
2. The testing of a joint hypothesis creates a problem as one would be unable to determine whether these results reflect that international markets are segmented or that the IAPT has failed.

2.2.2 Empirical Testing of the APT

Much of the research into the APT model focuses on its ability to outperform the CAPM or how many factors are optimal when seeking to explain returns in any given market. The flexibility of the APT has allowed academics to branch out beyond this type of research and begin to examine the real world applications of the APT. Empirical testing is essential to the APT because the theory itself is quite general. Although it states that several risk factors may affect returns, it does not specify the nature or the number of factors that should be utilised. Therefore, testing is required to ensure that the APT can be used in practical applications such as portfolio management. One of these real world applications is to use the APT framework to determine the drivers of a specific country's economy. This was the intention of the original Chen, Roll, and Ross (1986) research and since then, the concept has been applied in a number of different markets.

2.2.2.1 BRICS

In the Brazilian market, Hsing (2004) showed that GDP has a relationship with the stock market in both the short and long-term. Sorokina (2013) showed that money supply also has a significant relationship with the Brazilian stock market. Finally, a positive relationship between exchange rates and stock prices was found to be statistically significant in Brazil; this implies that an appreciation (depreciation) of the Brazilian Real would have unfavourable (favourable) impact on the Brazilian stock market (Gay Jr, 2008).

The nuances of the Russian market imply that risk factors, such as political risk (Goriaev & Sonin, 2004), and non-market factors such as affiliation with foreign partners and participation in unsavoury privatisation schemes in the past (Fedorov & Sarkissian, 2000) can also influence stock market performance. A positive relationship between the exchange rate and stock prices was also found to be statistically significant; this implies that an appreciation (depreciation) of the Russia Ruble would have unfavourable (favourable) impact on the Russian stock market (Gay Jr, 2008).

In India, there is a body of literature that has identified money supply, gold and silver prices, exchange rates, trade deficit, and the inflow of foreign investment capital as all having explanatory power in the Indian stock market (Singh D. , 2010; Naik & Padhi, 2012; Patel, 2012; Singh P. , 2014; Mohanamani & Sivagnanasathi, 2014). Gold, for example, tends to have an adverse effect on the Indian stock market due to the increasing interest in this commodity as an alternative form of investment. There is still a level of distrust in corporate, the Indian stock market as well as its regulatory bodies (Sehgal, Sood, & Rajput, 2009; Kavitha, 2015). This drives Indian investors to seek alternative investment instruments, much to the detriment of the development of the stock market. The exchange rate, mainly against the US dollar, also has a strong effect on the Indian stock market depending on the Rupee appreciation or depreciation against the US dollar. The reason behind this is simply the strong trade relationship between the two countries.

In South Africa, initial research into the macroeconomic APT was conducted by van Rensburg (1995) who first employed criteria for selecting appropriate macroeconomic factors, outlined by Berry, Burmeister and McElroy (1988)[3]; thereafter, van Rensburg (1995) employed a linear factor model to identify if unexpected changes in one or more of these variables are responsible for underlying returns on the Johannesburg Stock Exchange (JSE). This was accomplished by measuring the sensitivities of the JSE to the pre-specified variables, as done in Chen, Roll, and Ross (1986). The factors chosen include: returns on the Dow Jones Industrial Index, the gold price, inflation expectations, and the term structure of interest rates. The results indicated that all four macroeconomic variables were significant when regressed against market returns – the JSE is significantly influenced by the chosen macroeconomic variables. A natural extension to this study is to investigate whether these factors are 'priced' in the JSE. This was undertaken by van Rensburg (1996) who employed the iterated non-linear seemingly unrelated regression (ITNLSUR) methodology, first pioneered by McElroy and Burmeister (1988). The results showed that all the factors outlined above, except the gold price, were associated with statistically significant risk premia; this implies that they not only explain returns but are priced factors in the APT. The subtle difference between an explanatory factor and a priced factor lies in the fact that a priced factor provides compensation to the investor for taking on the risk, whereas an explanatory factor merely explains the variation in stock returns, for example. In this instance, the evidence found by van Rensburg (1995; 1996) illustrated that returns on the Dow Jones Industrial Index, inflation and the term structure of rates not only explain the variation in JSE returns but also provide investors with compensation, due to the risk inherent in these variables. These results are consistent with Chen, Roll, and Ross (1986), who found the same variables to be significant risk factors in the APT.

2.2.2.2 G7 Countries

In the German market, there is evidence that money supply and exchange rates could be used in explaining the German stock market (Masuduzzaman, 2012). Additionally, exchange rates, particularly between the Euro and other European currencies, could be especially useful due to

[3] Economic variables that are legitimate risk factors must possess the following three properties:

1. At the beginning of every period, the factor must be completely unpredictable to the market.
2. Each APT factor must have a pervasive influence on stock returns.
3. Relevant factors must influence expected return – they must have non-zero prices (Berry, Burmeister, & McElroy, 1988).

the degree of economic integration in the continent. Given the close proximity of countries, it is likely that other countries in Europe could have an impact on the German stock market.

In the UK, Masuduzzaman (2012) shows that exchange rates and money supply have significant and strong explanatory power in the UK market. Exchange rates of other countries in close geographical proximity to the UK, such as the rest of Europe, are likely to have an impact on the UK given the phenomenon of volatility spillover or the contagion effect. This is similar to what would be expected in Germany. There has also been evidence that indicates that money supply, the credit spread, and GDP growth have explanatory power in the UK market (Sarwar, Mateus, & Todorovic, 2015). Other research indicates that measures of corporate default, private sector bank lending, and the current account balance could also be priced risk factors in the UK stock market (Clare & Thomas, 1994).

Finally, in the US market monetary policy appears to have strong explanatory power in the market. Thorbecke (1997) uses three different methods to measure monetary policy: 1) Federal Reserve targeted non-borrowed reserves; 2) An index created using Federal Reserve open documents and records; and 3) Federal fund rate changes. All three measures were found to have a statistically significant effect on stock returns. Money supply, which is related to monetary policy, has also been shown to have an impact on market returns (Kraft & Kraft, 1977; Flannery & Protopapadakis, 2002). Moreover, commodities are usually viewed as an alternative investment mechanism and hence their prices could also have an impact on market returns – evidence to support this was uncovered by Kia (2003). Finally, indicators of the health of an economy have also been found to be priced risk factors in the US; specifically, balance of trade, employment (Flannery & Protopapadakis, 2002), and unemployment (Chang & Ha, 1997).

This section has highlighted that the APT framework has been used by many academics in guiding their research into the macroeconomic determinants of a specific economy. The evidence highlights that the factors outlined by Chen, Roll, and Ross (1986) do not necessarily encompass the full universe of factors which could possibly explain returns. Furthermore, it also highlights that there are differences across countries as what explains market returns in one country does not necessarily explain market returns in a different country. It is important to highlight that the focus of many of these research papers was to determine which macroeconomic factors could have explanatory power in a given market. This study, however, opts to use a uniform set of macroeconomic variables – those outlined by Chen, Roll, and Ross (1986) – for the following reasons:

- The basis of this study is fundamentally asset pricing; however a specific focus was put on the role of investor sentiment in explaining returns and not which macroeconomic factors have more explanatory power across different countries.
- Holding the macroeconomic variables constant allows for the full effects of investor sentiment to be isolated.
- A uniform set of macroeconomic variables allows for a comparison across the various countries, as any potential results could not be due to differences in explanatory variables.
- Uniformity allows for a comparison countries as the method applied should provide a much 'cleaner' result.

The APT has demonstrated itself as a model that is able to be applied in a real world context; it has proven to be useful in determining macroeconomic variables driving a country's economy. Although many have used the set of variables outlined by Chen, Roll, and Ross (1986); however, many country-specific factors have also been included and demonstrated themselves to have statistically significant explanatory power in explaining market returns. These include factors such as money supply, the gold price, GDP, and exchange rates. This is not unexpected as an individual country has its own history, characteristics and nuances which will impact the macro-economy. For the purposes of understanding the individual macroeconomic drivers of a country, applying this approach was useful; however, this study is focused on understanding the role of investor sentiment in explaining returns and hence a uniform data set is applied across all countries.

2.2.3 Statistical Testing of the APT

A critical component of developing an asset pricing model is determining the appropriate conditions for testing it; specifically, what conditions needs to be fulfilled to determine the empirical viability of the model and whether the model is robust in explaining returns.

An important consideration in any research focused on macroeconomic factors is the concept of endogeneity. Endogeneity refers to a problem encountered when a given explanatory variable is correlated with the error term of the model. It can be the result of a measurement error, omitted variables, or the nature of the variables (Wooldridge, 2013). The latter is likely to be true in this scenario as macroeconomic variables tend to be related to one another due to their role in the greater economy. As such, multiple macroeconomic explanatory variables are likely to be correlated and the resulting regression may suffer from endogeneity. Most commonly endogeneity is caused by: 1) An uncontrolled confounder (a variable which correlates with both the dependent and independent variable) which causes both the dependent and independent variables; and 2) A loop of causality between the independent and dependent variables in a regression model. If endogeneity is found in this analysis, it is likely that the latter is the primary cause. Endogeneity is identified by determining whether there is a statistically significant correlation between the residual of the model and each individual explanatory variable. Statistical significance would imply that that specific variable is endogenous, and statistical insignificance would imply that that specific variable is exogenous. In a model with purely exogenous variables, the OLS[4] regression would hold; conversely OLS breaks down in the event of endogenous variables and hence an alternative regression method is required.

Endogeneity is addressed through the application of the instrumental variables (IV) method and subsequently the Two Stage Least Squares (2SLS) method. IV involves replacing the dependent variables with predicted values of those same variables that satisfy the following two conditions: 1) Exogeneity: the IV must be uncorrelated with the error term of the model and 2) Relevance: the IV is correlated with the independent variable. Only once both these conditions are satisfied is a variable considered to be an IV. This process will ensure that a consistent regression coefficient is obtained. In the instance of one variable being found endogenous, only one instrument is necessary and hence this instrument can be included in a standard OLS regression. This is performed in two steps; step one involves obtaining the IV values and step two involves running an OLS regression, but replacing the endogenous variable with the IV estimator. In the event of multiple endogenous variables and hence multiple instruments, the 2SLS regression method is applied. The 2SLS method allows for the inclusion of instrumental variables. The output of this regression, specifically the coefficients and associated p-values, is the same as that derived from an OLS regression. The difference with

[4] OLS – Ordinary Least Squares. This is a method for estimating unknown variables in a regression model by minimising the sum of the squares of the differences between the observed and predicated data sets.

the 2SLS regression is that it allows one to test if the regressors are exogenous or not (Wooldridge, 2013).

The earliest application of IV involved attempts to estimate demand and supply curves; a number of economists were interested in estimating the elasticities of demand and supply for a wide variety of products using time series data. Given that demand and supply curves shift over time, the observed data on price and quantity reflects an equilibrium point on both curves. An OLS regression of quantity on price would fail to identify either the supply or demand relationship. Wright (1928) confronted this issue in a seminal application of IV with positive results; many academics have used this as a base for the application of IV to their specific research. Instances where IV has been used have not been limited to economics or finance, but can be found in the social and health sciences as well.

IV has been used to address the problem of endogeneity and omitted variables when estimating the impact of economic conditions on the likelihood of civil conflict in 41 African countries (Miguel, Satyanath, & Sergenti, 2004). Rainfall variation was used as an IV for economic growth, which is negatively related to civil conflict. The results indicated that the use of the IV was able to overcome the methodological problem of endogeneity and omitted variables and it was found that growth shocks have a statistically significant impact on the likelihood of civil war. IV has also found a use in evaluating the empirical relation between the level of financial intermediary development and economic growth and productivity (Beck, Levine, & Loayza, 2000). The IV estimator was used to extract the exogenous component of financial intermediary development; the result showed that financial intermediaries exert a large, positive impact on productivity which feeds through to overall GDP growth. Explaining firm-level investment behaviour through the use of an IV estimator was tackled by Hubbard, Kashyap, and Whited (1995) who used firm tax payments as an IV estimator as it minimises a measurement error which was identified. The results indicated that capital market imperfections and dividend pay-outs are statistically significant in explaining and effecting firm-level investment decisions.

The choice of how to model asset returns is also a statistical consideration; specifically one can apply either a linear or nonlinear model. A linear model assumes that the error term of the model is normally distributed; whereas a nonlinear model assumes that the error term is not normally distributed and hence accounts for this. The APT assumes that the risk-return relationship is linear in nature and hence there is no opportunity for arbitrage. If the risk-return relationship is found to be non-linear in nature then arbitrage is possible. That being said, any attempts to arbitrage will force linearity in the relationship between risk and return. As such, the APT can be modelled both linearly and nonlinearly. The choice of model depends in part on the choice of explanatory variables as well as what specifically is being modelled.

One such method of modelling the APT nonlinearly was employed by McElroy and Burmeister (1988) who replaced the unknown random factors of factor analysis with observed macroeconomic variables, as such they were able to recast the APT as a nonlinear regression model. The authors employed iterated nonlinear seemingly unrelated regression (ITNLSUR) to obtain the joint estimates of the asset sensitivities and their associated risk prices. The ITNLSUR technique overcomes many of the methodological problems experienced by other methodologies, such as loss of efficiency and un-robustness of the estimate if the errors were found to be non-normal. The choice of macroeconomic variables included the S&P500 index, an expected growth in sales, unexpected deflation, long-term government and corporate bonds, and a one month T-bill. The results were found to be in support of the nonlinear APT with measured macroeconomic factors; this indicates that the APT still holds its explanatory power even in nonlinearity.

The IAPT, discussed in Section 2.1.1.1, developed by Solnik (1974) was further developed upon by Bansal, Hsieh and Viswanathan (1993). The authors use a nonlinear APT model and both a conditional and unconditional linear model to price international equities, bonds, and forward currency contracts. The advantage with the nonlinear APT model is that it requires no restriction on payoffs and hence can be used to price the payoffs of options, forward contracts and other types of derivative securities. They presented results in support of the nonlinear APT as it was the only model able to explain the time series behaviour of a cross section of international returns. Further support for this approach was provided by Bansal and Viswanathan (1993) who do not assume a linear factor structure for payoffs. As such, the model was able to be used to price the payoffs of both primitive and derivative securities. The empirical results using size-based portfolio returns and yields on bonds reject the CAPM and linear APT models and support the nonlinear APT. Moreover, the diagnostics on the nonlinear model showed that it was more capable of explaining variations in small firm returns.

Reese (1993) employed a nonlinear approach to the APT on the JSE using the technique outlined by McElroy and Burmeister (1988). The author compiled a list of risk factors likely to affect shares, these included: gold price risk, growth rate risk, residual market risk, foreign exchange risk, inflation risk, and default premium risk. These were then tested separately against mining and industrial shares on the JSE; tests against the mining shares found that gold price risk and growth rate risk were priced risk factors in the APT, whereas tests against the industrial shares found that all risk factors considered were priced risk factors in the APT. The ITNLSUR method was found to be robust in that it was able to assist the APT in explaining the variation in stock returns.

Similarly, Bernat (2011) studied the impact of multiple pre-specified sources of risk on the return of three non-overlapping groups of countries using a nonlinear APT model, estimated using both the ITNLSUR and Generalised Method Moments techniques. Two strategies were employed to choose two sets of risk factors; the first uses macroeconomic variables prescribed by various sources of empirical literature and the second is to extract the factors by using a principal component analysis. The pre-determined macroeconomic factors include the market portfolio return, in this case the All Country World Index constructed by the MSCI, foreign exchange risk, the spread between LIBOR and a 90 US T-bill, and changes in the oil price. Moreover, five statistical factors were found as a result of the principal component analysis. A great resemblance was found between the first statistical factor and the world excess return implying that a world market portfolio is important in explaining the covariance structure of country returns. In both strategies employed, premiums associated with the world excess return were found to be robust. The other pre-specified risk factors were not necessarily prices, but did assist in reducing the absolute pricing error. Overall, the ITNLSUR approach with pre-determined macroeconomic factors was found to be the best-fit model across all groups.

Outside of the APT, nonlinear models have also proven to be superior in other instances. A nonlinear approach was also employed by Su (2012) in attempting to understand the relationship between the Renminbi (RMB) and macroeconomic variables in China. The RMB and various macroeconomic variables were found to have a nonlinear relationship which might have gone unnoticed if a linear model was employed. Nonlinear models are often used for forecasting purposes; Balcilar, Gupta and Kotzé (2013) applied this approach when forecasting macroeconomic data for South Africa. A nonlinear model was found to be statistically superior to a linear forecasting model. This has important policy implications as it highlights that when informing policy, one should seek to incorporate potentially important nonlinearities in the model structure.

Once a model has been developed and run, the robustness of said model should also be determined through various tests. Often this involves conducting various tests on the residual of the regression model. A unit root test, such as the Augmented Dickey Fuller or Kwiatkowski–Phillips–Schmidt–Shin test, is often conducted on the residual of the regression to test whether this series is stationary or non-stationary. If the residual series is found to have a unit root, the series is said to be non-stationary; this implies that the residual series has a time-varying mean, time-varying variance or both. This implies that an OLS regression is perhaps not the most suitable to describe the regression. The residual is further tested for normality; as mentioned above a normally distributed residual implies that the model, in this case the APT, can be described using a linear model. Should the residual be found to display non-normalities, a nonlinear methodology such as the ITNLSUR needs to be applied when generating the APT. Another robustness check involves testing whether the observations are serially correlated with one another; this determined through the Lagrange Multiplier test which tests for the presence of ARCH (Autoregressive Conditional Heteroscedasticity) effects. This test is conducted as an uncorrelated time series can still be dependent due to a dynamic conditional variance process; this implies that a time series exhibits conditional heteroscedasticity. Statistically significant ARCH effects would imply serially correlated residuals. Finally, regression stability diagnostics can be run to determine the presence of outliers in the model as well as how good of a fit the regression model is. These stability diagnostics will often include leverage plots and influence statistics; leverage plots provide an indication of goodness of fit of every explanatory variable to the fit line or regression line, whereas the influence statistics will provide an indication of the presence of outliers in the overall model as well as for each explanatory variable considered.

A final regression model robustness check dates back to Markowitz's (1952) work on the trade-off between the mean and the variance of risky assets. Ever since then the question of mean-variance efficiency of an asset or a set of proposed asset-pricing pricing factors has been greatly important to finance researchers and capital market participants. Early empirical testing relied heavily on asymptotic econometric tests on relatively short records of a small set of portfolios and individual stock returns. These challenges were addressed by Gibbons, Ross, and Shanken (1989) (GRS) who presented a finite sample test of mean-variance efficiency of one or a set of assets with respect to another set of basis securities; as such, reliable inferences could be made using a limited historical time series of returns. The GRS is applied in time series regressions when there are multiple portfolios to compare and determine whether the alphas of each portfolio are jointly equal to zero. Moreover, the statistical significance of the constant is jointly tested for a number of portfolios simultaneously.

Mathematically, the GRS test can be represented as follows:

$$GRS = \frac{(T - N - K)}{N} \frac{\widehat{\alpha}' \widehat{\Sigma^{-1}} \hat{\alpha}}{1 + \bar{F}' \widehat{\Omega^{-1}} \bar{F}} \sim F_{N,T-N,-K}(\eta) \quad \textbf{(9)}$$

Where $\bar{F}$ and $\widehat{\Omega}$ are the sample mean and covariance matrix of the excess returns on the K reference portfolios. The exact finite sample distribution, $F_{N,T-N,-K}$ is the F distribution with degrees of freedom N and $T - N - 1$ and non-centrality parameter $\eta = [T/(1 + \bar{F}' \widehat{\Omega^{-1}} \bar{F}] \, \widehat{\alpha}' \widehat{\Sigma^{-1}}$.

The GRS test has been employed in numerous asset pricing studies in determining whether a portfolio is efficient or not. Grinold (1992) employed the GRS test to determine whether equity benchmarks in the United States (S&P500), the United Kingdom (FTA), Australia (ALLORDS), Japan (TOPIX) and Germany (DAX) are efficient in terms of expectations. The results indicated that the first four indices were found to be efficient and only the DAX was found to be inefficient. The GRS test was also employed by Fama and French (1996) to test the efficiency of their three-factor model, outlined in Section 2.1.1. The GRS test rejected the hypothesis that their three-factor model explained the average returns on the 25 portfolios under consideration. Detzler and Wiggins (1997) sought to determine whether international funds that actively engage in country and security selection outperform passive global benchmarks; the GRS test was employed to test the efficiency of a variety of international mutual funds. One of the indices employed, a world equity index, was found to be inefficient under the GRS test, even after accounting for exchange rate risk; hence it cannot be used as an appropriate benchmark for testing a fund manager's ability. Moreover, a multi-country benchmark index was also found to be inefficient under the GRS test; however, when the short sale constraint was accounted for, the multi-country benchmark was found to be efficient. Chen, Novy-Marx, and Zhang (2011) develop an alternative to Fama and French's (1993) three-factor model. This model comprises of a market factor, an investment factor and a return on assets factor; the results indicate that it is able to explain many more patterns in the cross-sectional returns than the Fama and French (1993) model. The GRS was used in determining the robustness of this model against both Fama and French (1993) and CAPM; the author's three factor model is unable to be rejected by the GRS test, whereas both the Fama and French (1993) and CAPM are rejected under the GRS. This new three factor model was also useful in explaining other anomaly variables such as earnings surprises, total accruals, net stock issues, and asset growth. The empirical results as well as the GRS test indicate that this new three factor model is robust. The outcome of the GRS test has multiple applications and implications; it can determine the efficiency or robustness of an asset pricing model as well as for a given portfolio of assets. As such, it has implications for asset pricing theory as well as for active managers and capital market participants.

The GRS has demonstrated itself as a robust asset pricing test; however, the test is completely dependent on a uniform set of explanatory variables. Essentially the same set of explanatory factors should be used to jointly explain the returns on multiple portfolios. This study makes use of uniform data sets, but the data itself is different for each country. Employing the GRS test in this study would be ineffective as the GRS would, for example, test whether inflation in Germany affects ALSI returns in South Africa. Clearly, determining this would not provide an indication of the robustness of the individual country APT models. As such, the GRS test cannot be applied in this study.

This section has outlined the various considerations for the statistical testing of asset pricing models, particular the APT. Macroeconomic variables have a tendency to suffer from endogeneity – this problem occurs when an explanatory variable and the error term of the model are correlated. This problem is usually as a result of a measurement error, omitted variables, or simply the nature of the variables; if not addressed, the inclusion of endogenous variables can result in spurious regression results. The instrumental variable and 2SLS methods are often employed to address the problem of endogenous variables. A further statistical consideration of asset pricing models is whether they should be modelled linearly or nonlinearly. Nonlinear models tend to be less restrictive and can, in some cases, prove to be a superior asset pricing model. There is evidence to indicate that a nonlinear APT model may be superior to the linear alternative as there are fewer restrictions, especially about the payoffs. This implies that other asset classes, apart from equities, can be modelled under the APT. The choice of linear versus nonlinear, however, is completely dependent on the data being used. Once an asset pricing model has been developed, its robustness also needs to be tested using various tests. This involves checking that the residual of the model is stationary and normally distributed (non-normal residuals would indicate that perhaps a nonlinear model is more suited to the data set). Leverage plots and influence statistics can also be used to detect the number of outliers as well as the stability of the model. A final test that can be applied to an asset pricing model is the GRS test, which can be used to test the efficiency of an asset pricing model or a portfolio of assets. Both have implications and applications in the real world.

2.2.4 Summary

The APT was constructed to address the weaknesses of the CAPM, specifically its weakness in empirical testing as well as its unrealistic assumptions. Although the APT too is constructed using various assumptions, these assumptions are not as restrictive as those of CAPM. Fundamentally, the APT is a framework under which various factors can be used in explaining asset prices and their associated returns; as such, this makes the APT more flexible in nature. The APT, much like the CAPM, was also augmented to be used on an international scale. Unfortunately, empirical testing of the APT is grounded in a joint hypothesis that international markets are integrated and that the APT holds in an international context. The testing of this joint hypothesis creates a problem as one would be unable to determine whether the results reflect that international markets are segmented or that the APT holds internationally. As such, constructing an IAPT is not the focus of this study as it would not yield insights about the individual countries under examination. Much of the empirical research into the APT focuses on the correct number of factors to be used in the model, as well as what those factors actually are. The APT framework is also used to determine the macroeconomic drivers of a country's economy and stock market; the individual nuances of a country has a large impact on this as a factor that has explanatory power in one country may not have explanatory power in another. Finally, there are a number of statistical considerations when testing an APT model, including accounting for endogeneity, choosing the appropriate type of model, and ensuring the model is robust by conducting various robustness checks.

2.3 Behavioural Finance and Investor Sentiment

This section provides an overview of the history and beginnings of behavioural finance and then goes on to describe a specific concept of behavioural finance, investor sentiment. Investor sentiment is then examined in detail; its role in explaining theories and anomalies in investment theory is outlined as well as its role in explaining market returns, using various measurements of investor sentiment. Finally, another behavioural finance concept is examined – the asymmetric effects of investor reactions between positive and negative news.

2.3.1 A Brief History of Behavioural Finance

Investor sentiment is part of a much larger area of research field known as behavioural finance, which "is the study of the influence of psychology on the behaviour of financial practitioners and the subsequent effect on markets" (Sewell, 2010, p. 1). This concept is somewhat logical as ultimately it is people who are participating in market transactions; hence it would be reasonable to assume that an individual's mental attitude would affect their decisions and finally, financial markets. Behavioural finance, much like any new theory, was not developed overnight; instead it was built upon by academics from both finance and psychology fields.

Psychology of the Stock Market: Human Impulses Lead to Speculative Disasters written by George Selden in 1912 is the earliest manifestation of the combination of psychology and finance. This book was written on the premise that movements in prices on the exchanges are dependent on the mental attitudes of the investing and trading public. This in essence provides the foundation for investor sentiment as a concept.

Based on the foundation of Selden's book, it is clear that the mental attitudes of individuals will influence their decision making, hence affecting price movements on exchanges. An important aspect of decision making is the feelings and emotions one experiences when making a decision. Loewenstein (2000, p. 426) argues that these "often propel behaviour in directions that are different from that dictated by a weighing of the long-term costs and benefits of disparate actions." This can easily be related to financial markets as equity pricing involves weighing long-term benefits (the right to a share in future net cash flow due to an equity stake) and costs (the riskiness of the future cash flows) and hence it seems reasonable to hypothesise that emotions and feelings will influence their pricing of equities (Lucey & Dowling, 2005).

A psychological analysis of financial decision making would be incomplete without describing the role that risk plays. Risk refers to future uncertainty about deviation from expected earnings or an expected outcome. Holton (2004) argues that there are two ingredients that are needed for risk to exist; the first being uncertainty about the potential outcome and the second the outcome has to matter in terms of providing utility. Risk is an inherent component in any financial decision and investors will accept a certain degree of risk based on their specific risk profile, this implies a degree of asymmetry in risk profiles of individual investors. It is clear from the very nature of risk that it has an impact on financial decision making; however risk coupled with a framing bias suggests that an investors' degree of risk taking will be affected by how that individual frames their prospective gains or losses (Gärling, Kirchler, Lewis, & van Raaij, 2009).

Decision making under risk is a critical component in the development of behavioural finance; there are two models that are used to analyse this concept. The first being expected utility theory (EUT), followed by prospect theory; interestingly, the latter was developed as a critique to the former. EUT is based on four axioms that define a rational decision maker, each is described below:

1. Completeness: assumes that an individual has well-defined preferences and thus, can always decide between two alternatives.
2. Transitivity: assumes that, as an individual decides according to the completeness axiom, they do so consistently.
3. Independence: assumes that two gambles mixed with a third one maintain the same preference order as when the two are presented independently of the third one.
4. Continuity: assumes that if there are three gambles (A, B, and C) and the individual prefers A to B and B to C, then there should be a possible combination of A and C in which the individual is then indifferent between the mix and gamble B.

If the four axioms are satisfied, the individual is assumed to be rational and hence their preferences can be represented by a utility function. Essentially, this means that an individual will choose between risky or uncertain prospects by comparing the expected utility values (Anand, Pattanaik, & Puppe, 2008).

The downside with EUT is that it only holds when all four axioms are met. This is precisely the critique described by Kahneman and Tversky (1979) who present a number of classes of choice problems where EUT does not hold. As a result, EUT cannot be viewed as an adequate descriptive model and instead the authors develop prospect theory. Under prospect theory, value is assigned to gains and losses; also probabilities are replaced by decision weights. The value function, therefore, is defined by a deviation from a reference point with the type of deviation providing an indication of whether an individual is risk averse or risk seeking.

Decision making is largely an internal force – it is an individual's decision – that has the ability to affect financial markets. However, an external force has an impact on how an individual will react to something, which also has the ability to impact financial markets. Investor reaction, specifically overreaction, is something that was considered by DeBondt and Thaler (1985), with their research finding that individuals systematically overreact to unexpected and dramatic news events. The outcome of this research is viewed by many to be the beginning of behavioural finance.

2.3.2 Investor Sentiment

Many traditional finance models are underpinned by the assumption that the individuals participating in financial markets are rational. Rationality entails that investors, upon receiving new information, update their beliefs correctly in alignment with Bayes' Theorem[5] (Laplace, 1812) and investors make choices that are normatively standard, that is consistent with Savage's Subjective Expected Utility (Savage, 1954). However, given that an individual's mental attitude affects their decision making, it would appear that they do not necessarily update their beliefs and make choices in a rational manner – a manner that is free of emotion. In fact, given Loewenstein's (2000) view that emotions and feelings change an individual's behaviour and hence, cause them to make decisions that are different than what would be dictated by a cost-benefit analysis, it would appear that individuals tend to behave more irrationally than rationally.

By quantifying and studying investor sentiment, it allows one to see how an individual's beliefs affect financial markets. In essence, it provides a much more realistic view of the mechanics of financial markets.

The limitations of conventional finance theory gave rise to the study of behavioural finance, which seeks to understand the emotional processes of investors and how these processes influence their decision making – viewing the investor as irrational as opposed to rational (Ricciardi & Simon, 2000). The study of stock price movements that are seemingly unjustified by fundamental pricing theories can be attributed to the term "animal spirits" which was made popular by Keynes (1936).

[5] Bayes' Theorem describes the probability of an event, based on conditions that might be related to that event. This theorem was used to show how new evidence is used to update one's beliefs and was further developed and published by Laplace (1812).

2.3.3 The Role of Investor Sentiment in Investment Theory

The evidence outlined above has demonstrated that investor sentiment can be measured in a variety of ways and hence can be used to explain changes in financial returns. Essentially, the evidence considers investor sentiment in isolation and how it can explain financial returns. There is another aspect of investor sentiment that should be considered, and that is its role in explaining other theories or phenomena in investment theory.

Investment theory "encompasses the body of knowledge used to support the decision-making process of choosing investments for various purposes." (Goetzmann, 1996, p. 3). It includes a wide variety of topics which aim to understand how individuals and institutions make investment decisions; hence, a full understanding is not achieved until one understands broad investor behaviour. Many of these theories are founded on the concept of a rational individual; however, this is also the source of their weakness in empirical testing due to a gap where investor behaviour should be incorporated. Behavioural finance has found its way into a number of investment theories, such as the Efficient Markets Hypothesis and the CAPM. Investor sentiment, on the other hand, has played a role in explaining investor behaviour through the noise trader model, the CAPM, and the APT.

2.3.3.1 Noise Trader Theory

It has been debated quite extensively if uninformed investors or noise traders actually have an effect on financial assets. The neoclassical view is that an investor trading on anything other than fundamentals would fall prey to rational arbitrageurs and be forced out of the market. However, the work done by Black (1986) suggests that noise trading will persist in the market because it plays an important role in providing liquidity. As Black (1986, p. 530) put it: "Noise makes financial market possible, but also makes them imperfect. If there is no noise trading, there will be very little trading in individual assets." As such, it was critical that academics gain a clearer understanding of how traders acting on non-fundamental information could affect stock price; the first group of academics to do this was De Long, Shleifer, Summers and Waldmann (1990).

Their model assumed two classes of investors – those trading on fundamental information and those who trade on a noisy signal. Noise traders affect stock prices as they trade when they are unusually bearish or bullish. Thaler (1993, p. 18) describes the difference between rational and noise traders as follows: "One way to think about noise is that it is the opposite of news. Rational traders make decisions on the basis of news (facts, forecasts etc.). Noise traders make decisions based on anything else." If several noise traders act together, their trading will cause prices to deviate from fundamentals. Given that arbitrage is now a risk – deviations from fundamentals could increase – rational traders now opt not to correct the mis-pricing. As a result, noise traders have effectively created an additional source of systematic risk that is priced in the market. This risk should manifest itself as added price volatility of assets affected by noise traders. The short-run and long-run impact of noise traders are addressed through various theories; in the short run, the 'price pressure' and 'hold-more' effect; and in the long run, the 'Friedman' and 'create-space' effect. The 'hold-more' effect implies that noise traders increased their holdings of risky assets when their sentiment is bullish, thus raising market risk which increases expected returns. Noise traders tend to overreact to good and bad news and hence asset prices are either too high or too low depending on their sentiment. This overreaction introduces 'price pressure' and lowers expected returns. Moreover, noise traders usually have poor market timing and hence their capital losses are larger the greater their misperceptions are. The 'Friedman' effect implies that these changes result in higher market risk and lower expected returns. Finally, the extent of the 'Friedman' effect on expected returns depends on the 'space' noise trading creates. A rise in noise traders' misperceptions increases price uncertainty and crowds out risk-averse informed investors. So, the larger the proportion of noise trading the higher the expected returns will be (Lee, Jiang, & Indro, 2002). The fact that noise traders will trade when they are either extremely bullish or bearish implies that they are experiencing a level of either positive or negative sentiment which is then influencing their decision making.

Testing the presence of noise traders involve ascertaining whether there is a relationship between investor sentiment and volatility. Brown (1999) tests the four hypotheses outlined by De Long, Shleifer, Summers and Waldmann (1990), however specific to closed-end funds. Specifically: 1) If sentiment is not fund specific, discounts on closed-end funds should be correlated; 2) Discounts should be a measure of sentiment; 3) New closed-end funds should be offered primarily when sentiment is overly bullish; and 4) Extreme levels of sentiment should be associated with noise trading and therefore an increase in volatility. Brown (1999) uses the AAII survey as well as closed-end fund discounts to determine if this relationship does in fact exist. Changes in investor sentiment were found to be associated with fund volatility during trading hours; this is expected as noise traders should only affect prices through their trading activities. The number of trades as well as the average size was also found to be affected by investor sentiment; the number of trades increased with unusually bullish or bearish sentiment, with the average size of the trade decreasing. The most important conclusion from this research was that investor sentiment was found to be a statistically and economically significant variable in explaining trading activity – this bodes well as it provides support for the noise trader theory.

The impact of noise trader risk on both the formation of conditional volatility and expected return is examined by Lee, Jiang and Indro (2002). The authors employ the II survey and jointly test the four behavioural effects outlined by De Long, Shleifer, Summers and Waldmann (1990). The authors found that shifts in sentiment are negatively correlated with the market volatility; that is, as volatility increases (decreases) when investors become more bearish (bullish). Investor sentiment playing a significant explanatory role on conditional volatility implies that conventional measures of temporal variation in risk omit noise as an important factor.

Further support for the noise trader theory is provided by Verma and Verma (2007) who investigate the relative effects of fundamental and noise trading on the formation of conditional volatility. This study extends upon that of Brown (1999) as it considers both individual and institutional investor sentiment; individual investor sentiment is measured by the AAII survey and institutional investor sentiment is measured by the II survey. Market performance is characterised by the DJIA and the S&P500. Their evidence was in favour of irrational sentiment explaining volatility which is consistent with the view that investor error is a significant determinant of stock volatility. The direct implication, however, is that conventional measures of temporal variation in risk omit an important source of risk: noise. Therefore, noise can be seen as a priced risk factor. By extension, this supports the notion that investor sentiment plays a role in the noise trader theory in investment theory.

Noise trader theory is fundamentally based on investor sentiment and that investors, who are either experiencing bullish or bearish sentiment, will trade based on their sentiment. Moreover, noise traders rarely act in isolation implying that when a number of them trade, the price of an asset is driven away from fundamentals which ultimately results in mis-pricing. Normally, arbitrageurs would act on this and any mis-pricing would be effectively traded away. However, what actually happens is that rational traders do not correct the mis-pricing which causes an additional systematic risk which is priced. Noise trader theory gives a clearer understanding of how irrational individuals, driven by their sentiment, behave in the market and what implications this has for risk and return.

2.3.3.2 Modifications of the CAPM

The CAPM was discussed in detail in Section 2.1.1 where it was highlighted that the CAPM has come under criticism for its unrealistic assumptions, particularly that the model assumes all investors behave in an identical and rational manner. There are two important iterations of the CAPM which account for irrational investors and introduce psychological biases; the Behavioural Asset Pricing Model (BAPM) developed by Shefrin and Statman (1994) and a Sentiment CAPM (SCAPM) developed by Yang, Xie and Yan (2012).

The BAPM was developed by Shefrin and Statman (1994) to allow for the presence of noise traders. The authors developed a CAPM in a market where noise traders, who do commit cognitive errors, interact with information traders, who are free of cognitive errors and base their decisions purely on fundamental data. The authors contend that the distinguishing factor between a price efficient market, where CAPM holds, and a price inefficient market, where abnormal returns are achieved, is the single driver property. This is the minimal amount of new information necessary to infer changes to the return distribution of the market portfolio. A noise trader would introduce a second driver into the market and hence drive prices away from efficiency. Moreover, the effect of noise traders in the market depends crucially on the type of errors they commit. Their theory encompassed a behavioural mean-variance theory, a behavioural option pricing theory, and a behavioural term structure theory. In a price efficient market, security prices are determined through a single driver, a sufficient statistic consisting of only new information. This single driver then drives the mean-variance efficient frontier, the return distribution of the market portfolio, the premium for risk, the term structure, and the price of options. Moreover, the volatility of the long-term interest rate is zero. However, when prices are not efficient, new information is no longer a sufficient statistic. Old information will still affect prices, volatility, risk premium, term structure and option prices. However, the effect of noise traders is not uniform across securities or time. Noise traders will have a larger impact on the term structure than the return on the market portfolio and can also distort option prices.

Yang, Xie and Yan (2012) present the SCAPM which shows the relationship between sentiment perceived risk and sentiment perceived return. The authors derive a sentiment capital market line (SCML) as follows:

$$R_{ps} = \mu_f + \frac{R_{Ms} - \mu_f}{\sigma_{Ms}} \sigma_{Ps} \tag{10}$$

Where R_{ps} is the sentiment perceived return on portfolio P, μ_f is the risk-free rate, R_{Ms} is the sentiment perceived return on the market portfolio, σ_{Ms} is the sentiment perceived risk of the market portfolio, and σ_{Ps} is the sentiment perceived risk of portfolio P.

As well as a sentiment securities market line (SSML) as follows:

$$R_{is} - \mu_f = \frac{\sigma_{iMs}}{\sigma_{Ms}^2}\left(R_{Ms} - \mu_f\right) = \beta_{iMs}(R_{Ms} - \mu_f) \qquad \textbf{(11)}$$

Where R_{is} is the sentiment perceived return on risky asset i, μ_f is the risk-free rate, σ_{iMs} is the covariance of risky asset *i* with tangency portfolio *M*, σ_{Ms}^2 is the sentiment perceived risk of the perceived market portfolio, and β_{iMs} is the sentiment beta

Equations (10) and (11) together form the SCAPM. The authors then compared these models with traditional asset pricing models as well as the BAPM. The results of the testing of the SCAPM revealed that an investors' individual sentiment will lead to different SCMLs and SSMLs, which will lead to the investor having different perceived prices. The comparison with CAPM showed that the optimistic investor will have a higher perceived price, and the pessimistic investor will have a lower perceived price; thereafter, trade will occur between these parties. Based on this, the excessive trading anomaly can be interpreted using the SCAPM. When compared with the Fama and French (1996), it was found that investor sentiment is a key factor in asset pricing and that the sentiment beta in SCAPM can be easily determined. Finally, the comparison with BAPM yielded a challenge as the β in BAPM is the sum of the β in CAPM and the risk of noise traders. Unfortunately, the risk of noise traders is difficult to determine which makes the behavioural β in CAPM difficult to measure, whereas SCAPM's sentiment beta can be easily determined.

Unfortunately, there is a lack of empirical evidence to support the behavioural finance augmentations of the CAPM. Nevertheless, the fact that theories have been developed which take into account both behavioural finance and investor sentiment is positive. It indicates that there is a role that investor sentiment can play in explaining asset returns.

2.3.3.3 APT

The APT is discussed in detail in Section 2.2 and is the subject of this particular study as it allows for flexibility in the choice of factors used in the model. The flexibility of such a framework also breeds significant challenges; specifically, the number of factors to be included in the model as well as which factors. Nevertheless, such a flexible approach that is not hindered by the assumptions like CAPM should provide us with more insight. Including factors into the APT which incorporate behavioural finance concepts should also yield a greater understanding of asset prices.

Building on the macroeconomic foundation of Chen, Roll and Ross (1986), Hasan (2010) includes a measure of investor sentiment to the model as a means to improve its explanatory power. The results of Hasan's (2010) macroeconomic APT were poor in that only the change in expected inflation was found to be statistically significant in explaining returns. Chen, Roll and Ross (1986), on the other hand, found strong significance in four of the factors and somewhat weaker in two factors. This caused Hasan (2010) to re-evaluate and consider that there might be some other risk factors which could affect stock prices. The rationale behind incorporating an investor sentiment component was based on the fact that investors are becoming more well-informed and hence are able to make educated guesses about stock returns. As such, consideration was given to a variable that would capture the behavioural aspect of investors. Once this component was included – as measured by the Conference Board CCI – the joint significance of all six factors was improved. Overall, the explanatory power of the macroeconomic model improved. This indicates that investor sentiment does capture a risk factor which affects stock returns and a behavioural approach to the APT could yield a more holistic understanding of asset pricing.

The five-factor macroeconomic model developed by Chen, Roll and Ross (1986) was further built upon by Shen and Yu (2013) who developed an 11-factor model which incorporates investor sentiment. The macroeconomic factors includes consumption growth, total factor productivity, industrial production growth, term premium, default premium, unexpected and expected changes in inflation, aggregate market volatility, market returns, and labour income growth. Market-based investor sentiment is measured using the Baker and Wurgler (2006; 2007) index. During periods of low sentiment, it is hypothesised that markets will be more rational and efficient and high risk firms should earn higher returns as sentiment-driven investors require larger compensation during this time. Evidence was found to support this hypothesis, implying a degree of rationality that is present. However, during periods of high sentiment it is hypothesised that the opposite will be true. Evidence was also found to support this hypothesis; during periods of high sentiment, high risk firms earn lower returns than low risk firms as sentiment-driven investors do not require as much compensation during this time. Therefore, it appears as though mis-pricing plays a role in understanding asset returns and that it is important to incorporate investor sentiment into economic theory and asset pricing models.

The APT as a data return generating process can also be viewed as a framework to explain asset prices and their associated returns. As such, it provides the opportunity to gain an understanding of the role irrational investors plays in explaining asset prices and returns. There is evidence that indicates that investor sentiment captures additional risk that may influence asset prices. Moreover, investor sentiment tends to cause mis-pricing in the market which also appears to be an important factor in understanding asset prices; the effects of mis-pricing also appear to be more pronounced during periods of high sentiment.

A critical component of the definition outlined in the introductory paragraph is that investment theory involves understanding decision making. As such, a proper understanding involves understanding the role of irrational behaviour in making such decisions. The noise trader model is one manifestation of investor sentiment in investment theory; it provides an understanding of those traders who trade on information other than fundamentals and hence cause mis-pricing in the market, which also results in greater volatility in asset prices. The CAPM and APT are two of the fundamental asset pricing models in investment theory; both are used to understand the driving factors behind asset prices and returns. The CAPM has been built upon to include such concepts at behavioural finance and investor sentiment which helps in understanding the role investor sentiment plays in explaining asset prices (see BAPM and SCAPM in Section 2.3.3.2). Moreover, the APT which is a framework for determining asset prices allows for a variety of factors to be used, including investor sentiment – similar to the topic of this study. The evidence has indicated that asset price explanations through the APT can be improved through the inclusion of an investor sentiment component. The role of investor sentiment in these various investment theories indicates that a more holistic understanding of investment decisions can be achieved by considering the behaviour of irrational investors.

2.3.4 The Role of Investor Sentiment in Understanding Returns

Inherent in the study of behavioural finance is the challenge of quantifying the concepts that lie within its realm. Investor sentiment, specifically, poses a challenge in that one is trying to quantify an individual’s beliefs, expectations and thoughts. Moreover, investor sentiment can be defined as either direct or indirect. Direct investor sentiment refers to investors' mood or expectations about the future and is usually measured via surveys and questionnaires that measure investors' current financial conditions as well as their expectation of the future (Uygur & Taş, 2012). Indirect investor sentiment refers to a number of economic variables that are perceived to act as proxies for measuring investor sentiment (Uygur & Taş, 2012).

Despite the challenge in measuring investor sentiment, there has been progress in the evolution of how it is measured. The traditional method is measurement by way of surveys, whereby a number of questions will assess an individual's expectations of the future of the economy as well as their future purchasing power. This remains a commonly used tool as it gathers data directly from individuals and is seen to represent the general wellbeing of a country.

Investor sentiment can also be measured, indirectly, through a number of market variables. These market variables are merely proxies of investor sentiment; however, a number of market variables have strong theory to support their use as proxies for investor sentiment. The clear downside of using market variables as proxies is that they are just that – proxies; they do not directly capture the beliefs or expectations of individuals.

A further source for measuring investor sentiment is through media, specifically traditional media such as newspaper and magazine articles as well as through social media platforms such as Twitter or Facebook. Extracting investor sentiment from media generally involves textual analysis – analysing the words that are used to capture sentiment. Historically, this was done through traditional media sources, but has now evolved to include various social media platforms. This method is advantageous for two reasons: investor sentiment can be extracted directly from individuals which means much richer data, and with the extent of worldwide media and the popularity of social media, it allows for a variety of sources to be used.

An extension to the use of media involves the use of Internet message boards; this method also employs textual analysis to analyse posts that have been made on these message boards. An advantage of this method is that you are likely to gather sentiment data from informed individuals based on the choice of message board. For example, gathering sentiment data from a finance-related message board, such as Yahoo! Finance, to use in financial empirical analysis implies that the sentiment data would be drawn from informed individuals as they are active participants in financial markets.

Regardless of how it measured, empirical evidence clearly indicates that investor sentiment has a significant relationship with asset returns, whether explanatory or predictive. Empirical evidence using each measure is outlined below.

2.3.4.1 Surveys of Investor and Consumer Sentiment

Early evidence of the use of surveys to measure investor sentiment was documented by Solt and Statman (1988) who constructed the Bearish Sentiment Index (BSI), the ratio of the number of investment advisors who are bearish to those who are either bearish or bullish, and tested its validity as an indicator of future stock prices. The BSI is seen as a contrary indicator, meaning that one should buy when investment advisors are bearish and sell when they are bullish. The data is sourced from Investor Intelligence (II), an investment service in New York that published data based on a survey of sentiment advisory newsletters. Investor opinions are classified as either bullish or bearish; this task is challenging however II standardises its classification criteria and personnel used from week to week. This indicator was then tested against the Dow Jones Industrial Average (DJIA) to determine the impact it would have. The sample period was chosen dependent on the investor sentiment data; the sample period runs from January 1963 to September 1985, amounting to a total of 1 000 observations. The results showed that the BSI was a useless indicator of future stock price changes, with the number of correct forecasts by the index equalling the number of incorrect forecasts. This result then begged the question: If the sentiment index has little or no predictive power, why do people continue to believe that it is useful? The authors provided two suggestions as to why this could be the case, both due to errors in cognition. The first is failure to recognise randomness and the second is the illusion of validity. Failing to recognise randomness originates from the belief in the "hot hand" in basketball. It is believed that a player is more likely to score a hit after a hit than after a miss. Although empirical evidence has refuted this theory, spectators, players and coaches persist in their beliefs. This explanation was investigated by the authors who found that changes in the DJIA during a period are unrelated to the level of the sentiment index – this indicates changes in the DJIA conditional on the sentiment index were found to be completely random, consistent with the Random Walk Hypothesis. The illusion of validity occurs when people experience confidence in highly fallible judgement (Kahneman & Tversky, 1973). This tends to persist because people suffer from a confirmation bias where people seek confirmation of hypotheses rather than disconfirmation and hence will selectively search and interpret financial information (Hilton, 2001). Specific to this research, the investment advisors did indeed suffer from the illusion of validity and confirmation bias.

An important outcome of the noise trader model developed by De Long, Shleifer, Summers, and Waldmann (1990) is that it predicts that the direction and magnitude of changes in noise trader sentiment are relevant in asset pricing. Lee, Jiang and Indro (2002) found that evidence relating to this outcome was at best incomplete and hence sought to test the four behavioural effects in the noise trader model. Instead of using closed-end fund discounts as a proxy for investor sentiment, the authors opted for using the II sentiment index as a direct measure of investor sentiment. Furthermore, they tested the relationship between investor sentiment and excess returns using three different market indices, namely the DJIA, S&P500 and the NASDAQ. The relationship was tested for the entire sample period, as well as over a number of sub-periods. The authors employed a GARCH model to show that not only excess returns, but also conditional volatility, are affected by investor sentiment. Overall, investor sentiment was found to be a significant factor in explaining both conditional volatility and excess returns. Specifically, sentiment was found to be a priced risk factor; excess returns are contemporaneously and positively related to shifts in investor sentiment. Moreover, the magnitude of the shift has a significant impact on the formation of conditional volatility and expected returns. The significance of investor sentiment in explaining conditional volatility and excess returns was found to hold across the various indices and sub-periods.

Research conducted by Otoo (1999) in the United States examined the relationship between movements in consumer sentiment and stock prices as well as delving deeper to examine the nature of the relationship between the two. The study made use of the Michigan Consumer Sentiment Index (MCSI) as the measure of consumer sentiment and the Wilshire 5000 stock price index as a proxy for the overall market. The sample period spanned from 1980 to 1990 and monthly data was utilised. A significant and strong contemporaneous correlation between the two variables was found; although the relationship was found to be fairly robust, stock prices explained only 10% of the variation in consumer sentiment. In order to determine if there was a leading or lagging relationship between the variables, Granger causality[6] tests were employed. The outcome of the causality tests suggest that stock price movements affect changes in consumer sentiment, but lagged changes in consumer sentiment have no explanatory power for stock prices. Thus, it can be concluded that stock price movements are a leading indicator for changes in consumer sentiment. In order to examine the nature of the relationship,

[6] Granger-causality is based on predictability and considers the direction of the flow of time to determine the causal ordering of the chosen variables (Granger, 1969).

Otoo (1999) sought to answer the question, "Does an increase in stock prices raise aggregate sentiment because people are wealthier (wealth effect) or because they use stock price movements as an indicator of future economic activity and potential labour income growth (leading indicator)?" This question was answered using observations on individuals; the micro-data has the advantage of endogeneity, as no single individual's level of sentiment would affect the entire US stock market. The results provided strong support for equity prices being used as a leading indicator of economic activity as stock price movements appeared to have a greater impact on individuals' assessments of business conditions. Although the evidence of a traditional wealth effect was found to be weak, it cannot be ruled out completely.

The research conducted by Otoo (1999) was then built upon by Christ and Bremmer (2003) who used three additional stock indices to understand the relationship between consumer sentiment and stock price movements. In addition to the Wilshire 5000, the DJIA, the S&P500 and the NASDAQ were used as proxies for the US market. Consistent with Otoo (1999), consumer sentiment was measured via the MCSI. All data sets consist of a monthly time series, covering a sample period of 1978 to 2003, with the exception of the NASDAQ whose data is available from 1984 to 2003. Cointegration tests were performed and it was found that there was no long run relationship between the measure of consumer sentiment and the equity indices. Given the outcome of no long run relationship between the variables, the short run relationship was examined using Granger-causality tests. The outcome of these tests revealed that changes in equity prices as measured by the four equity indices Granger-caused changes in consumer sentiment, consistent with the outcome from Otoo (1999).

A European perspective was provided by Jansen and Nahuis (2003) who analysed 11 European countries from 1986 to 2011. Theirs was the first look into the effects of consumer confidence in the European market and as such, presented valuable insight from which to draw inferences. The consumer confidence indicator used was published by the European Commission for all EU countries excluding Luxemborg. The data is collected on behalf of the European Commission by various national institutes during the first 10 working days of the month. The surveys are harmonised, that is a uniform questionnaire is used across all countries, and results are seasonally adjusted. The questionnaire consists of four questions which gather public views regarding future household position, future economic situation in the country, future unemployment in the country and planned savings behaviour going forward. The countries included in the sample are: Belgium, Denmark, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, Spain and the UK. The nature of their study was twofold, first they analyse the relationship between the stock market and the aggregate consumer confidence index and second, they disaggregate the consumer confidence index into its components to provide insight into the nature of the relationship. Their results were positive in that they found a positive correlation between the two variables for nine countries, with Germany being the only country showing a disconnection. At a country level, they found that the UK demonstrated the highest correlation between these variables, while the remaining countries revealed lower correlations. These results can be said to reflect the fact that stock ownership in continental Europe is significantly lower than in the UK (Boone, Giorno, & Richardson, 1998). Moreover, they found that stock returns Granger-cause consumer confidence at short horizons, but not vice versa. Their further analysis found that the stock market-confidence relationship is driven by expectations about economy-wide conditions rather than personal finance. This suggests that the confidence channel is based on the leading indicator property of stock prices, and that it is not part of the conventional wealth effect. These results are largely consistent with the outcomes of research conducted by Otoo (1999) and Christ and Bremmer (2003).

Similar analysis to Jansen and Nahuis (2003) was conducted by Karnizova and Khan (2010) in the Canadian market from 1961 and 2008 with similar results. The Canadian measure of consumer confidence is published on a quarterly basis by the Conference Board of Canada, and is based on a survey of Canadian households. The index combines responses to questions about current and expected personal financial position, employment prospects and current buying conditions. The S&P Toronto Stock Exchange (TSX) composite is the primary indicator for Canadian equity markets. This data is extracted on a monthly basis and subsequently converted to quarterly by using the values in the last month of each quarter, consistent with the timing of the Conference Board Survey. The results found that changes in the stock and consumer confidence index are positively correlated, and that stock market changes Granger-cause consumer confidence index changes, consistent with the outcome of research conducted by Jansen and Nahuis (2003) in Europe. Stock market movements can influence consumer consumption through changes in wealth (the wealth channel), or indirectly by influencing consumer confidence (the confidence channel) – the results of this research provided support for both hypotheses.

Charoenrook (2005) examines whether investor sentiment has any bearing on asset returns, by using the MCSI. Excess market returns are calculated using the CRSP market indices minus the one-month return of the Treasury bill that is closest to its 30 day maturity. These indices include shares listed on the AMEX, NYSE and NASDAQ. The outcome of this result was that changes in consumer sentiment are positively related to contemporaneous excess market returns and negatively related to future excess market returns. Moreover, changes in sentiment predict value-weighted and equal-weighted excess market returns at one-month and one-year horizons.

Further evidence of surveys used to measure investor sentiment can be found in the Australian market. Lin, Ho and Fang (2005) examine investor sentiment's influence on the stock market in two stages. Firstly, they examine if investor sentiment captures any variation in market returns and secondly, they assess its predictive power on subsequent stock returns. The Australian consumer confidence indicator is compiled from the responses to five questions that address different aspects of respondents' attitudes toward economic outlook. The five questions include the family financial situation over the past year, the expected changes in the family financial situation over the next year, the expected changes in economic prospects in the next year and the next five years, and the views on the buying conditions of major household items. Market returns are obtained from the S&P/ASX 300; moreover, based on the S&P classification there are 11 economic sectors in Australia. The authors documented that changes in consumer sentiment are positively related to aggregate returns. At a more granular level, it was found that energy, financials excluding property trusts, industrials, information technology and materials sectors are highly influenced by swings in sentiment. The reason behind this result is that these sectors tend to be characterised by less stable cash flows and are more subjective in their valuation. In tracing the source of the sentiment, it was found that the most important factor in the sentiment measure is the perception of next year's economic condition. Their main finding is that public confidence in the short-term provides explanation for the variation in returns that cannot be explained by other variables. The second part of their analysis showed that consumer sentiment seemed to lack predictive power on subsequent aggregate returns for most of the sectors. This results support the outcome of Charoenrook's (2005) research conducted in the USA.

Lemmon and Portniaguina (2006) made use of the MCSI and the Conference Board Index of Consumer Confidence (CBIND) in order to assess the extent to which sentiment affects the prices of shares in times of optimistic and pessimistic assessment of market conditions by investors. Their analysis covered both rational and behavioural channels through which investor sentiment might be manifested in asset prices. First, consumer confidence was regressed against a set of macroeconomic variables (default spread, dividend yield, GDP growth, consumption growth, labour income growth, the unemployment rate, the inflation rate and the consumption-to-wealth ratio). The residual from the regression was used as a measure of excessive sentiment (optimism or pessimism) unwarranted by fundamentals. The authors then employed lagged measures of fundamental and sentiment components of consumer confidence to explore the time-series behaviour of the betas and pricing errors for returns on a portfolio of long shares in the smallest decile and short shares in the largest size decile. It was found that, for the two decades under observation, consumer confidence exhibited forecasting power for the returns on small shares and for future macroeconomic activity. The sentiment component of confidence was found to forecast time-series variation in the size premium. When tested against the closed-end fund discount or the Baker and Wurgler (2006) composite measure of investor sentiment, there was no strong relation found indicating that the different measures either capture some unrelated components of investor sentiment or fail to capture some important aspects of investor sentiment. The puzzling result that emerged was that the relationship between consumer confidence and subsequent stock returns and macroeconomic activity was non-existent prior to 1977; this can possibly be attributed to the changing dynamics of participation of households in equity markets. Regardless, their evidence suggests that in recent years, consumer confidence has become a much better indicator of economic activity and investor attitudes.

Lux (2008) investigated the causal relationship between investor mood and subsequent stock price changes in the German stock market. The author made use of sentiment survey data provided by Animus X, who provide a range of technical services and information for German investors. The market data used is that of the German stock price index, the DAX. The results highlighted the apparent informational inefficiency in the German stock market. The anonymously collected sentiment of a large number of individual and institutional investors has produced an overall indicator that has significant predictive power for near-term returns. The medium term sentiment measure is highly predictable and hence cannot be seen as a measure of new fundamental measure; rather it is seen as the slowly moving basic mood of the market that has very weak links to returns. The results using the medium term sentiment measure are hardly reconcilable with the notion of efficiency or the traditional noise trader model. In contrast, short-term sentiment shows alignment with the noise trader model as it performs wild, short-lived swings between euphoria and depression.

An international perspective is offered by Schmeling (2008) who examines how investor sentiment, proxied by consumer confidence surveys, predicted the returns for eighteen industralised countries. The countries included in this sample are the US, Japan, Australia, Japan, New Zealand, Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Netherlands, Norway, Spain, Switzerland and the UK. The choice of markets was dictated by data availability; however the chosen markets do capture the largest share of international stock market capitalisation and cover the most liquid markets in the world, namely the US, Europe and Japan. In addition to the consumer confidence surveys collected for each country or region, monthly returns were gathered for the aggregate stock market, a portfolio of value shares and a portfolio of growth shares. It was found that the predictive power of investor sentiment is most pronounced for short and medium term horizons of one to six months and washes out for longer horizons of 12 to 24 months. Some international differences were picked up as the predictive power of investor sentiment varies across countries and in some cases investor sentiment contains no predictive power for several countries at all. These results are consistent with the findings of Jansen and Nahius (2003) who also provided insight into the relationship between investor sentiment and stock returns on an international scale. A cross-sectional analysis was conducted with the purpose of delving deeper into the differences found. The influence of noise traders was found to provide an economically intuitive explanation. The impact of investor sentiment on returns is much higher for countries that are more prone to herding behaviour and those countries that have less efficient regulatory institutions or less market integrity. The international evidence from Jansen and Nahuis (2003) and now, Schmeling (2008) demonstrate that one cannot simply transfer insights from the US to other markets and presume that noise traders move shares in general. It is important to note that institutional quality and cultural factors are strong determinants in the investor sentiment-stock return relationship.

A different perspective is taken by Chen (2011) who examines whether the effect of shocks to consumer confidence on stock returns varies during different phases of the market cycle and whether decreased consumer confidence leads to a bearish stock market. The persistent lack of consumer confidence in the US since the 2008 subprime crisis has attracted a lot of attention and has led to concern over the effect of pessimism on the economy and stock market. The sample period spans from 1978 to 2009, the MCSI is used as the measure of consumer confidence and the S&P500 stock price index is used due to the focus on the US stock market. In order to measure a shock to consumer confidence variables such as the unemployment rate, CPI (inflation is constructed via CPI), the Federal Funds rate and real output measured by industrial production are included into a regression with the MCSI. A variety of Markov switching models were applied to characterise the fluctuation in the stock market and identify the impact of market pessimism on stock returns and the switching behaviour between bull and bear markets. The author found strong evidence indicating that the lack of confidence has an asymmetric effect on stock returns. As was predicted, the impact is much greater in bear markets. They also showed that the greater the market pessimism the higher the probability of switching from a bull to bear market; moreover, a direct relationship was found between the severity of market pessimism and the time with which the market stays in a bear regime.

Ho and Hung (2012) provide an international perspective of the predictive capabilities of investor sentiment measures in eight developed countries. The countries included in this sample are the United States, the United Kingdom, France, Germany, Italy, Japan, Australia and New Zealand. Investor sentiment measures unique to that particular country were used in the analyses. In the US, the MSCI, the CBIND and the II surveys were used. For the European countries, the consumer confidence indices specific to a country are used, these are developed by the European Commission. In order to capture information not contained in the consumer confidence indicators, the Economic Sentiment Index (ESI), which measures the investment-GDP growth relation, for European countries was also used. Consumer confidence indices are used as measures of investor sentiment in the Asia-Pacific countries; these indices adopt similar questions and calculation procedures to that of the MSCI. The major stock market index in each country was used to measure market performance; monthly returns were collected from the S&P500, FTSE100, CAC40, DAX30, MIB30, NIKKEI225, ASX20, and MZ50CAP. The fundamental information contained in the sentiment measures is controlled by using the dividend yield, inflation rate, T-bill rate and the rate of change in industrial production. It was found that consumer confidence exhibited predictive power for the subsequent stock market returns in the US, France and Italy where high consumer confidence predicts low excess stock market returns; this finding of a negative relationship is consistent with prior research (Fisher & Statman, 2000; Brown & Cliff, 2005) . An exception is found in Japan where the current consumer confidence level boosts the excess market return the following month; in this case a positive relationship was found. Finally, the ESI showed no predictive ability for return on the European markets.

Molchanov and Stangl (2013) investigate the effects of investor sentiment on industry returns using industry portfolios constructed by Fama and French. The Fama and French industry classification maps all NYSE, AMEX and NASDAQ shares to one of 49 industries using the S&P Industrial Classification. Their analysis also employs two direct measures of sentiment, namely the American Association of Independent Investors (AAII)and II surveys, as well as an indirect measure, namely the index created by Baker and Wurgler (2006). The II survey reflects the sentiment of financial newsletter writers, with the sentiment of the writers being classified as bullish, bearish or neutral. Although this is a subjective process, Brown and Cliff (2004), have argued that the II survey proxies the sentiment of professional investors as many of newsletter writers are retired institutional investors. The analysis uses a bull-bear spread for both the AAII and II surveys, calculated as the difference between the reported measure of bullish and bearish sentiment. The Baker and Wurgler (2006) index is the indirect measure of sentiment which is constructed using closed-end fund discounts, NYSE stock turnover, the number of IPOs, first day average returns on IPOs, the percentage of equity in capital budgets and the dividend premium between dividend-paying and non-dividend-paying firms. Market data is extracted for all stocks listed on the NYSE, AMEX and NASDAQ. The primary result of this research is that investor sentiment positively predicts short-term and negatively predicts long-term market returns; the result also confirms that equal-weighted indices in which small shares have a greater weight are more susceptible to investor sentiment. At an industry level, the results document widespread investor sentiment predictability of industry performance for most industries; at long horizons, investor sentiment predicts negative industry performance.

In South Africa, the only publicly available CCI is compiled and published by the Bureau of Economic Research on a quarterly basis. It is measured via consumer surveys which provide regular evaluations of consumer attitudes and expectations which are then used to evaluate economic trends and prospects. The survey is constructed using three questions, each carrying a different weighting; the CCI is then computed as the average of the result of the three questions. The CCI is expressed as a net balance, therefore revealing changes in consumer expectations. The net balance is derived as the difference between the percentage of respondents expecting an improvement, and those expecting a decline (Kershoff, 2000). The CCI was employed by Solanki and Seetharam (2014) who studied consumer confidence and its effect on the Johannesburg Stock Exchange (JSE). JSE monthly price data was extracted for all companies listed on the JSE for the time period 1992 to 2011. In order to match the time period of the two sets of data, a time-averaging methodology was employed whereby the high frequency data (JSE stock returns) is matched to the low frequency data (CCI data). An Artificial Market Index (AMI) is created on a price-weighted basis from the JSE stock return data. As a comparable index, data for the All Share Index (ALSI) was also obtained. Granger causality tests are employed to investigate the relationship across time between the CCI, the AMI and the ALSI. The results show weak evidence of a contemporaneous relationship;

however significant evidence of a Granger caused relationship is apparent. Moreover, changes in investor sentiment Granger-cause changes in the AMI and ALSI generally with a lag of 9 or 12 months, but the reverse was not found to be true. Thus, it was found that the CCI lead JSE performance during the sample period; this is seen to be contradictory to the common perception of consumer confidence lagging market performance.

Surveys primarily serve as a direct measure of investor sentiment; it is advantageous in that the data, investors' beliefs and expectations, is gathered directly from the source and not proxied by other variables. The effect of investor sentiment on stock price performance has been reported in numerous countries, using a variety of different investor sentiment surveys. There are, however, a number of downsides to using surveys. Firstly, the information content of surveys tends to vary from question to question implying that certain surveys will be more useful than others, as such there is no level of uniformity in this measure (Friesner, Khayum, & Schibik, 2013). Secondly, the data is sourced directly from the consumers who have been known to suffer from a number of psychological biases. This implies that the results provided might be clouded by their judgement in terms of what answers they feel they should provide versus the actual truth. Finally, differences in measurement across surveys make comparing the results quite challenging. Nevertheless, investor sentiment surveys have allowed academics to gain important insights into financial markets and enabled further research into this topic.

2.3.4.2 Market Variables

Surveys are a direct measure of investor sentiment; however, it can also be measured indirectly using market variables as proxies for investor sentiment. These market variables can be used as proxies as they capture behaviour in the market that is viewed to be investor sentiment driven. As such, investor sentiment became a tool employed to explain anomalies that were not easily explained using conventional finance theory.

2.3.4.2.1 *Mutual Fund Flows*

One such example is the closed end fund puzzle. A closed-end fund is a mutual fund which typically holds publicly traded securities. Unlike an open end fund, a closed-end fund issues a fixed number of shares that are traded on the stock market. To liquidate a holding in a fund, investors must sell their shares to other investors rather than redeem them with the fund itself for the net asset value (NAV) per stock as would be the case in an open-end fund. The closed-end fund puzzle is the empirical finding that closed-end fund shares typically sell at prices not equal to the per stock market value of the assets. Although funds sometime sell at a premium to their NAV, in recent years a discount of 10 to 20 % have become the norm (Lee, Shleifer, & Thaler, 1991). There have been a number of proposed explanations of the closed end fund puzzle, including agency costs, illiquidity of assets, and tax liabilities; however much of the empirical evidence often fails to explain this anomaly. Zweig (1973) originally theorised that discounts on closed-end funds reflect expectations of individual investors; this theory was supported by the "noise trading" model developed by De Long, Shleifer, Summers and Waldman (1990). The rationale behind this theory is that fluctuations in investor sentiment can lead to fluctuations in demand for closed-end fund shares which is reflected in changes in discounts; Lee, Shleifer and Thaler (1991) sought to provide further insight into the closed-end fund puzzle using these theories. The closed end fund data was obtained from 1960 to 1987, a total of 68 funds were used. For these funds, the weekly NAV per stock, stock price and discount per stock was collected from the Wall Street Journal. The conclusion from the research is that closed end fund discounts are a measure of individual investor sentiment; moreover, that sentiment is sufficiently widespread to affect the prices of smaller shares in the same way that it influences the prices of closed end funds. Apart from the empirical evidence, all the characteristics of the closed end fund puzzle can be explained through the effects of investor sentiment:

Characteristic one: Closed end funds start out with a premium of almost 10% when organisers raise money from new investors and purchase securities

Explanation: Holding the closed end fund is riskier than holding its portfolio directly, and because the risk is systematic, the required rate of return on fund shares must be higher than the same assets purchased directly. This means that the fund must sell at a discount to its NAV to induce investors to hold the fund's shares.

Characteristic two: Although closed end funds start at a premium, they move to an average discount of over 10% within 120 days from the beginning of trading

Explanation: When noise traders are particularly optimistic about closed-end funds, entrepreneurs can profit by combining a number of assets into a closed end fund and selling them to the noise traders. Rational investors would not buy these funds in the beginning and hence irrational investors need to be introduced into this model to explain why anyone would buy the shares at the beginning when the expected returns over the next few months is negative.

Characteristic three: The discounts on closed end funds are subject to wide fluctuations over time

Explanation: Investor sentiment implies that the discounts would fluctuate with changes in investor sentiment about future returns. In fact, the theory required that discounts vary stochastically as it is those precise fluctuations in the discount that make holding the fund risky and therefore account for the underpricing. If the discounts were constant then arbitrageurs would buy the fund and sell its portfolio and the discounts would disappear

Characteristic four: When closed end funds are terminated through either liquidation or an open-ending, the stock prices and discounts shrink

Explanation: When it is known that the fund will be open-ended or liquidated, or even when the probability of open-ending increases, the noise trader risk is eliminated as at that time an investor can buy the fund and sell its portfolio with guaranteed profitability. As a result, the closed end fund discount disappears.

Neal and Wheatley (1998) investigate the predictive power of three popular proxies of investor sentiment: the closed end fund discount, the ratio of odd-lot sales to purchases and net mutual fund redemptions. In addition to these three metrics, market capitalisation data was collected to be used in conjunction with the fund discount data. The data was collected for a 60 year sample period, from 1933 to 1993. A value-weighted index was constructed using the fund discount and market capitalisation data. The odd-lot purchases and sales are obtained on a monthly basis and thus are temporally aggregated to create an annual series to match the discount data. Their analysis was based on the return behaviour of two size-based NYSE-AMEX decile portfolios; these are value-weighted portfolios and are formed on the basis of the market value of equity at the beginning of each year. Their analysis produced somewhat mixed results. It was found that fund discounts and net redemptions do predict the size premium, the difference between small and large firm returns, but little evidence that the odd-lot ratio predicts returns. With regards to whether sentiment measures provide information to predict the size premium beyond what is contained in its stock price, net redemptions do provide additional information that is both statistically and economically significant.

Loss aversion is a psychological bias that many individual investors are subjected to and hence this is an important factor in measuring investor sentiment. This is the approach that Feldman (2010) employed when testing how an index that measures loss would perform in explaining contemporaneous and future medium term returns. The Perceived Loss Index (PLI) was originally developed by Friedman and Abraham (2009) by incorporating two insights from behavioural finance. Firstly, investors suffer from loss aversion, meaning that investors are affected by losses more than gains. Once an investor experiences a loss, they become more pessimistic about the reward/risk prospects; loss aversion only subsides once an investor experiences gains. Secondly, investors tend to place greater weight on the most current performance; they remember the most current losses and forget losses from the past. Feldman (2010) augments the original model by using market variables as the input, specifically, mutual fund data is used. The PLI is created from data from more than 14 000 mutual funds and focuses on an exponential average of current and realised losses. A number of other sentiment measures were included in the study; these included the MCSI and the Baker and Wurgler (2006; 2007) index. The results provided evidence that the PLI outperforms both the MSCI and Baker and Wurgler (2006; 2007) index in predicting future medium run returns, especially for one- and two-years horizons. This evidence was true not only for the broad market but also for capitalisation style and sector specific returns. In separate analyses, it was found that the PCI is a robust quantitative tool in detecting bubbles and financial crises in financial markets.

The use of mutual fund flow data as a proxy for investor sentiment, first investigated by Lee, Shleifer and Thaler (1991), was employed by Chi, Zhuang and Song (2012) in the hopes of shedding some light on the role of investor sentiment in the Chinese stock market. The authors opted to focus on individual shares as opposed to the aggregate market. Quarterly data was obtained for the five year sample period, from 2004 to 2008. The evidence out of China was found to be contradictory to much of the existing empirical evidence (where if sentiment pushes a security price above its intrinsic value, high-sentiment shares should earn low subsequent returns). Chinese evidence indicated that high-sentiment shares earn higher subsequent returns than low-sentiment shares. Insight into the Chinese stock market can be gained from Drew, Naughton and Veeraraghavan (2003) which is especially necessary when interpreting these results as this stock market is considered an emerging capital market. Specifically, 60 million investors own shares in China with an almost total absence of domestic institutional trading. Domestic institutional ownership, although a portion of overall market capitalisation (21%), is a completely non-tradeable category held by state-controlled investment trusts. Moreover, a portion of the market capitalisation is completely state-owned (38%), which is also a non-tradeable category. This implies that the majority of the Chinese stock market is non-tradeable. Regarding the investors, many participants are retail investors driven by a lack of alternative investment opportunities. The view of these investors is that they lack a level of financial sophistication and hence tend to rely heavily on rumours, making this market largely momentum driven. Evidence has shown us that certain markets react more severely to the effects of investor sentiment (Baker & Wurgler, 2007) and the nuances of this specific market may be explanation for the contradictory results highlighted above.

Mutual fund flows are, once again, used as a proxy for investor sentiment; specifically, shifts between bond funds and equity funds, known as net exchanges to equity funds, are used. This is popular proxy for investor sentiment as it measures the frequency with which investors shift their funds between the two instruments based on their beliefs about market movements. Ben-Raphael, Kandel and Wohl (2012) use data of mutual fund flows from 1984 to 2008; the aggregate data contains 33 categories: five for domestic equity funds, four for international equity funds, four for mixed funds and 20 for bond funds. Market data is measured by a value-weighted index composed of NYSE, Amex and NASDAQ shares. In addition to this data, Fama-French portfolios ("small stocks", "big stocks", "high book-to-market stocks", and "low book-to-market stocks") and the returns on the Russell 1000 and 2000 indices are used. The monthly aggregate net exchanges are related to contemporaneous changes in the stock market. Approximately 85% of this contemporaneous relation is reversed within four months, with the remainder being reversed within 10 months. The net exchanges were found to be negatively related to VIX (implied standard deviation of S&P 500 options); however the price reversals were too large to be explained by time-varying risk premia. As such, net exchanges can be interpreted as an indicator of investor sentiment. Consistent with this hypothesis, the effect was found to be stronger in smaller shares and growth shares which is also consistent with conclusions drawn by Baker and Wurgler (2006). It appears as though this measure of investor sentiment captures a different dimension of investor sentiment than other measures that have been used. Finally, this evidence supports the notion of "noise" in aggregate market prices that is induced by investor sentiment.

Beaumont, Frijns, Lehnert and Muller (2014) used Lee, Jiang and Indro (2002) as a foundation for their investigation into the relationship between investor sentiment and market returns. Similar to their predecessors, the authors opted to test the relationship against three different indices: the DJIA, S&P 500 and the NASDAQ 100. In contrast, the authors opted for an indirect measure of investor sentiment instead of a direct measure as was used by Lee, Jiang and Indro (2002); daily mutual fund flow data was used. The results, regardless of the choice of investor sentiment metric, were consistent with Lee, Jiang and Indro (2002) in that investor sentiment was found to have significant explanatory power for excess returns. Moreover, a strong positive relationship between investor sentiment and excess returns across all indices was found.

2.3.4.2.2 *Baker and Wurgler Index*

Baker and Wurgler (2006) built upon the findings of Lee, Shleifer and Thaler (1991) and used a number of proxies, including the closed end fund discount, as proxies for investor sentiment. The authors sought to investigate the effect of investor sentiment on the cross section of stock prices by using a number of practical proxies for investor sentiment; the methodology employed in measuring investor sentiment has since been used by numerous academics. The reason for using proxies is due to the fact that identifying cross-sectional patterns of sentiment driven mispricing is difficult and hence they chose to examine whether cross-sectional predictability patterns in stock returns depend on proxies for beginning-of-period sentiment. Apart from the closed end fund discount which is grounded by empirical research, the approach to proxies was practical in nature. The proxies included trading volume measured by NYSE turnover (TURN), the dividend premium (PDND), the closed-end fund discount (CEFD), the number and first-day returns on IPOs (NIPO and RIPO respectively) and the equity stock in new issues (S). A principal component analysis was employed in order to create an index of sentiment levels as well as an index of sentiment changes. The levels index is the first principal component of the six proxies and similarly, the changes index is first principal component of the changes in the six proxies. Monthly stock returns between 1963 and 2001 are used and formed into equal-weighted portfolios based on firm characteristics. It was shown that the cross-section of future returns is conditional on beginning-of-period sentiment proxies. With respect to firm characteristics it was found that when sentiment is estimated to be high, shares that attractive to speculators and unattractive to arbitrageurs – young, small, unprofitable, non-dividend paying, highly volatile, growth and distressed shares – tend to earn relatively low subsequent returns. However, when sentiment levels are low these cross-sectional patterns completely reverse. Baker and Wurgler (2007) built upon their previous research and sought to explain specifically, which shares are likely to be most affected by sentiment. Their results suggested that the same types of shares are more susceptible to broad waves of investor sentiment. The reason being these shares tend to be harder to arbitrage and they are more difficult to value, making biases more insidious and valuation mistakes more likely.

The Baker and Wurgler (2006; 2007) sentiment index is a simple, straightforward measure that has shown positive results in quantifying the effects of investor sentiment. It has filled a huge void in the literature in terms of quantifying investor sentiment by use of market variables. As a result, it has become a popular measure used in numerous academic journals spanning across multiple countries. The ability of this index to be replicated in other countries with promising results further commends its usefulness and robustness. Some of the international evidence is provided below:

- Analysis is performed on a global and local scale when Baker, Wurgler and Yuan (2012) constructed investor sentiment indices for six major stock markets and decomposed them into one global and six local indices. The purpose of this research was twofold: firstly, to investigate the effect of global and local components of investor sentiment on major stock markets, at the level of both the country average and the time series of the cross-section and secondly, to consider whether and how sentiment spreads across markets. The data is drawn from 1980 to 2005, covering Canada, France, Germany, Japan, the United Kingdom and the United States. In order to provide a degree of external data validation not found in existing literature, dual-listed shares are used. These are pairs of shares that claim equal cash flows but trade in different markets and sometimes at substantially different prices. The authors document that twins' relative prices are positively related to the relative local sentiment indices of their respective markets, proving the empirical validity of their indices. They also found that investor sentiment affects the time series of international market-level returns as well as the time series of the cross-section of international returns. Global sentiment was found to be a significant contrarian predictor of market returns. Both global and local components of sentiment help to predict the time series of the cross-section; namely they predict high returns on highly volatile, small, distressed and growth company shares. Finally, they found that investor sentiment appears to be contagious across markets and one of the mechanisms that drive this is international capital flows.
- Evidence in the Chinese market is provided by Huang, Yang, Yang and Sheng (2014) who examine the relationship between investor sentiment and stock returns on an industry-specific level. Country-specific market information is sourced from 2005 to 2013 and divided into 23 industries. Their results showed that investor sentiment is positively correlated with the current period industry return and negatively correlated with that for one period lagged. Moreover, the investor sentiment coefficients for the current level are greater than those for one period lagged, indicating a one-period price overreaction in the Chinese stock market – evidence that is consistent with the overreaction hypothesis outlined by De Bondt and Thaler (1985). In their secondary

analysis using a two-state Markov switching model, it was found that investor sentiment has a different effect on different industries' returns during different states of the market.

Staying with the study of developing markets, Dash and Makahud (2013) saw the need to understand the role of investor sentiment in a developing market such an India. The Indian market specifically has a high level of institutional and promoter ownership and low levels of retail investor participation and thus will provide out of sample insight into the effects of investor sentiment. The choice of sample period, from 2003 and 2011, was conditional on the availability of the required data. The authors extracted monthly returns for companies listed on the National Stock Exchange (NSE) in India, with the only exclusion being financial companies. The sentiment index was constructed using an approach similar to Baker and Wurgler (2006; 2007); however the authors extended the number of market variables to 11. The list of variables includes turnover volatility ratio, stock turnover velocity, advance decline ratio, change in margin borrowing, buy-sell imbalance ratio, put-call ratio, number of IPOs, equity issue in total issue, dividend premium, fund flow and cash to total assets. The results show that investor sentiment accounts for the cross-sectional variation in stock returns, even after controlling for market, size, book-to-market, momentum and liquidity factors. Moreover, the negative pricing effect of sentiment risk is attributable to the fact that positive sentiment results in an overvaluation the shares and hence lower subsequent returns are expected. An interesting insight is that despite the characteristics of the Indian market it is not a special case for sentiment driven mispricing; this is promising as it highlights that research into developing markets is yielding results consistent with those in developed markets.

Corredor, Ferrer and Santamaría (2013) analysed the investor sentiment effect in four key European stock markets: France, Germany, Spain and the UK. This particular study made use of the Baker and Wurgler (2006; 2007) index as well as composite indices of the four countries. This was done to account for the fact that this study was conducted in Europe, while Baker and Wurgler (2006; 2007) conducted their study in the US. These composite indices were constructed using three market variables: turnover, the volatility premium and the consumer confidence index as published by the European Commission. This research bears similarity to the work by Jansen and Nahuis (2003); specifically the markets under consideration and the use of the consumer confidence index. In addition to the country-specific indices, an overall European index was also created using the four composite indices. All indices were constructed in accordance with the Baker and Wurgler (2006; 2007) methodology of principal component analysis. Financial market data pertaining to all shares currently or formerly listed in the four markets was extracted for the period from 1990 to 2007, thus removing any potential survivorship bias. The stock characteristics considered were book-to-market, size (market capitalisation), volatility and dividend per stock. Investor sentiment was found to have a significant effect on the future returns of shares in these financial markets. Furthermore, consistent with Baker and Wurgler (2007) this effect was more pronounced for shares that are hard to value and more costly and risky to arbitrage. Stock characteristics were found to have explanatory power with respect to cross-country differences in sentiment effects; factors such as cultural or institutional differences also played a very key role. This is an important conclusion as the results of studies involving several countries may be biased unless these two dimensions were controlled for, as both are sources of investor sentiment. Finally, the choice of sentiment proxy was found to be a determining factor of the relationship as the results from the Baker and Wurgler (2006; 2007) index were the clearest in revealing the investor sentiment effect. The choice of variables for the construction of the proxy also played a key role as the explanatory power changed when the input variables changed. It is possible that the US market is a greater generator and spreader of investor sentiment or that the quality of the data used to construct the European indices lacks sufficient richness.

The methodology employed by Baker and Wurgler (2006; 2007) was employed by Dalika and Seetharam (2015) who created a Baker and Wurgler (2006; 2007) index for South Africa, using a combination of factors employed by Baker and Wurgler (2006; 2007) as well as alternative variables. Their analysis was also extended to include understanding which stocks would have greater reactions when sentiment was either higher or lower. The market proxies include a volatility premium, IPO volumes, first day returns on IPOs, number of IPOs, and market turnover. The volatility premium was not employed by Baker and Wurgler (2006; 2007); however, it was included due to the theoretical prediction that sentiment has its strongest effects on hard to value and hard to arbitrage stocks. Each of the market variables was then orthogonalised against three macroeconomic variables: inflation, employment growth, and industrial production growth. The results indicated that investor sentiment has a strong impact on stock returns in SA. When sentiment is low, subsequent returns are relatively high on smaller stocks, high volatility stocks, extreme growth stocks, and young stocks. Conversely, when sentiment is high, the patterns are fully reversed. This result is broadly consistent with the results uncovered by Baker and Wurgler (2006; 2007).

2.3.4.2.3 *Liquidity and Trading Volume*

An anomaly similar to that of the closed end fund puzzle is the concept of market liquidity and its effects on expected returns. Investors anticipate having to sell their shares at some point in the future and recognise that when this occurs they will face transaction costs. When the transaction costs are greater, investors rationally discount the asset by more. Although this explanation is straightforward, it becomes less clear when trying to explain time series results for the aggregate market. Firstly, it is unclear what drives the common time series variation in measures of liquidity and secondly, the predictive power of aggregate liquidity for market returns is large. Baker and Stein (2004) propose an alternative theory to explain the connection between liquidity and expected returns. Specifically, they focus on why time-variation in liquidity, at a firm or market level, might forecast changes in returns. Their model rests on short sales constraints and irrationally overconfident investors. Overconfidence manifests itself in two ways in this model: firstly, when overconfident investors receive private signals, they tend to overweight them which leads to either positive or negative "sentiment shocks"; secondly, when overconfident investors observe the trading decisions of others, they tend to underreact to the information contained in these decisions as they (erroneously) consider others to be less informed than they are. This lowers the price impact of trades and boosts liquidity in general.

Trading volumes are often seen as a proxy for investor sentiment; a modified trading index was used by Rahman, Shien and Sadique (2013) to provide insight into a frontier market such as Bangladesh. The noise trader model developed by De Long, Shleifer, Summers and Waldman (1990) was tested in this market using data from the Dhaka Stock Exchange. There are a number of reasons for choosing a frontier market such as Bangladesh: firstly, compared to a developed market, the Bangladesh capital market is not as well organised and managed. The market is largely driven by unsophisticated individual retail investors who are information constrained, lack the ability to process financial information and do not have the advice of financial analysts. As such, investment decisions of these investors are likely to be swayed by swings in investor sentiment. As presented by Schmeling (2008) the impact of investor sentiment on stock returns is higher for countries which have less market integrity and prone to herd-like behaviour and overreaction. Secondly, arbitrage opportunities in this market are severely limited as there is a complete short sell band and no derivative market. Due to the limited level of sophistication in this market, it is no surprise that market variables must serve as proxies for investor sentiment. In this case, a modified trading index is used as a proxy; this is a measure of relative strength of trading volume in relation to advancing shares against that of declining shares. The results showed that irrespective of the state of the market, daily excess returns are positively and contemporaneously related to shifts in investor sentiment. This result is consistent with much of the evidence uncovered in numerous developed and developing countries.

2.3.4.2.4 *Other*

A novel idea for a measure of investor sentiment was pioneered by Lutz (2013) who aggregated returns on lottery-like shares to measure investor sentiment. The shares used were speculative shares with high betas; these are high risk, high return shares. The returns on these shares were controlled for the effect of macroeconomic variables and measures of time-varying risk measures. In general, these lottery-like shares have less information available which allows investors to defend a wide range of valuations. They are also very risky to arbitrage due to the high idiosyncratic volatility and hence lottery-like shares are classified as highly speculative. If the findings from Baker and Wurgler (2007) are applied to this context, it is expected that these shares will be more susceptible to broad waves of sentiment as they are harder to arbitrage and more difficult to value. The outcome of this research was consistent with previous research in that high sentiment relates to low future returns over their entire sample period (1951 to 2009). In sub-period analysis, it was found that the effects of investor sentiment were weak but positive during trough-to-peak episodes of investor sentiment (sentiment expansions), but negative and large in peak-to-trough periods (sentiment contractions). These findings suggest that the relationship between returns and investor sentiment is highly asymmetric. Overall, the findings were found to correspond with investor sentiment theory involving synchronisation risk where arbitrageurs take long positions as sentiment expands and attempt to reduce their holdings of speculative securities when sentiment contracts. As an aside, it was found that the effects of sentiment were stronger after 1978, which supports the theory that a number of social factors led to increased sentiment since the early 1980s.

Research from the African continent, specifically in the Tunisian market, was conducted by Boubaker and Talbi (2014). The focus was on using indirect indicators to construct a sentiment index, using principal component analysis. Over a 4 year period (2004 to 2008) monthly data on premium volatility, dividend premium and the index performance were extracted. The Tunisian financial market has some peculiarities in that there are a limited number of companies listed and the market is dominated by large companies in the financial sector. Despite the idiosyncrasies in the market, a strong negative relationship was found to exist between investor sentiment and future returns. Essentially, a high-sentiment stock was found to have lower subsequent returns and sentiment drives the price of the security away from its fundamental value. This relationship is consistent with previous empirical evidence and highlights that anomalies found in developed markets can also be found in developing markets.

There are a number of market variables that have proven useful as proxies of investor sentiment. As mentioned above, survey data, although useful and insightful, is plagued with a number of nuances; hence the need for alternative measures. Using market variables has the advantage that the information is correctly measured, often independently collated and readily available through various databases. The most notable of these proxies is the closed end fund discount, the Baker and Wurgler (2006; 2007) index, mutual fund flows, book to market and market capitalisation. When tested against stock price performance, these variables demonstrated significant explanatory power as well as predictive power. Although these proxies are indirect measures of investor sentiment, they do still provide valuable insight into the role that investor sentiment plays in financial market performance.

2.3.4.3 News and Social Media

Survey information and market variables are but a few of the measurements of sentiment that can be used to explain "animal spirits" in the stock market. Cutler, Poterba and Summers (1989) pioneered research into the link between news and stock prices when they sought to estimate the fraction of returns that can be attributed to different kinds of news. Firstly, the authors studied the relation between stock returns and macroeconomic news using vector regressions. They found that these news proxies were able to explain about one third of the variation in stock returns. Due to the possibility that the stock market can move in response to information that did not enter their vector regressions, the authors then considered stock performance coinciding with major news events. The evidence indicated that although identifiable world news such as news about wars, the US Presidency and major changes in financial policies did affect stock prices, the authors find it implausible that "qualitative news" can account for the return component that cannot be traced back to macroeconomic news. Their evidence supported the observation that many of the largest market movements occurred on days when there were no major news events. This research opened opportunities for other to pursue research into the relation between news and financial markets.

In the development of this area of research, Tetlock (2007) attempted to characterise the relationship between the content of media reports, specifically the *Abreast of the Market*

(AOTM) column in the Wall Street Journal and daily stock market activity. This column was seen as a natural choice as a data source as it reflects and influences investor sentiment due to the WSJ's impressive circulation figures and its strong and established relationship with investors. The sentiment indicator was constructed using the General Inquirer (GI) methodology which converts the column into numeric values, which is it counts the number of words in each day's column that fall within various word categories. The word categories are neither mutually exclusive nor exhaustive – one word may fall into multiple categories while others may not be categorised at all. The results show that high levels of media pessimism robustly predict downward pressure on market prices, followed by a reversion to fundamentals. Interestingly this relationship is bi-directional meaning that low market returns lead to high media pessimism. The outcome of this research is important for two reasons: firstly, measures of media content can serve as proxies for investor sentiment and secondly, it provides support for the "noise trading" theory outlined by De Long, Schleifer, Summers and Waldman (1990).

As an extension to Tetlock (2007), Tetlock, Saar-Tsechansky and Macskassy (2008) sought to quantify the language used in financial news stories in an effort to predict accounting earnings and stock returns. The authors investigated the impact of negative words in all WSJ and Dow Jones News Service stories for individual S&P 500 firms from 1980 to 2004. Their primary result was that negative words convey negative information about firm earnings, beyond stock analysts' forecasts and historical accounting data. This implies that qualitative verbal information does not merely echo traditional measures of firm performance but provides value and insight not captured by firm fundamentals. A second result was that the stock market exhibits a delayed response to the information embedded in negative words on a subsequent trading days. As a result, potential profits could be earned by basing trading strategies on the words used in these publications. Further investigation focused on analysing negative words in news stories whose main content focused in firm fundamentals. It was found that negative words in stories about firm fundamentals predicts earnings and returns more effectively than negative words in other stories. These three findings highlight that linguistic media content captures aspects of firm fundamentals that are: 1) Hard to quantify and 2) Quickly incorporated into stock prices.

Textual analysis was employed by Ferguson, Guo, Lam and Philip (2011) in examining the relationship between media sentiment and stock returns in the UK. The authors sought to shed some light on the UK market as differences between media coverage in the US and UK have been well documented (Shaw, 1999). Specifically, US media was found to have much greater conformity, whereas the UK media has much greater dispersion of opinion and media independence. Given these findings, it would be incorrect to assume that the evidence that has been widely documented in the US is consistent across other countries. Using stock returns for FTSE 100 companies over the period 2005 to 2010 as well as news articles from the Financial Times, FT.com, The Times, Guardian and The Mirror, Guo, Lam and Philip (2011) investigated the presence of return predictability inherent in media sentiment. In total, just over 23 000 media articles were used in the analysis that covered 68 FTSE 100 companies. The use of textual analysis allowed the authors to create a positive and negative measure of media sentiment based on the fraction of positive or negative words in a given news article. It was found that positive (negative) media sentiment in company-specific news articles has a significant positive (negative) relationship with stock returns. This relationship was found to be stronger on the day the news articles were published. When testing for stock return predictability on the day following the publication of news articles, it was found that only measures of negative media sentiment contained significant predictive power, consistent with Tetlock, Saar-Tsechansky and Macskassy (2008). These results suggest that the UK market is fairly efficient at incorporating information and sentiment contained in media articles into stock prices; most media sentiment was incorporated into stock prices the day the articles were published. The fact that there was a trace of return predictability due to negative media sentiment indicates some cognitive dishonesty towards bad news by investors, resulting in some underreaction on the day of media publication; this is consistent with Grossman and Stiglitz (1980) as the underreaction to negative news provides motivation to monitor financial results and news.

Uhl (2011) made use of Reuters news articles to create a measure of investor sentiment, that is a positive or negative feeling, opinion, or emotion induced in a reader while reading a certain Reuters news article. This measure of investor sentiment was used to ascertain whether it could explain changes in stock market prices, specifically using the Dow Jones Industrial Index. The majority of textual analysis is conducted by simply coding positive and negative words into a database and matching the content of news articles to words in this database. This study attempts to replicate the work of Tetlock (2007); however Uhl (2011) felt that his General Inquirer tool was limited in that it is only able to account for negative words, but neither positive words nor the context of the article. The methodology employed by Thomson Reuters takes this analysis one step further by taking into account the context in which the article was written. This improved methodology is in itself a significant contribution to the existing literature on measuring investor sentiment. The dataset from Thomson Reuters consists of high frequency sentiment rated Reuters news pieces, classified from a wide list of topics pertaining to the US market. It was concluded that markets were not fundamentally efficient as positive correlations were found between negative (positive) sentiment and declines (gains) in stock returns; negative sentiment was observed to possess much stronger explanatory power than positive sentiment. Moreover, behavioural factors, such as Reuters sentiment, was found to explain stock returns better than fundamental factors.

Although there is evidence of a relationship between media coverage and financial markets, the relationship is sometimes labelled as purely speculative and the research is often based on circumstantial assumptions that make drawing inferences particularly difficult. Nonetheless, it is worth highlighting that although the media is often labelled as a faceless institution, its primary output – news articles – are written by people. The creativity inherent in writing allows an author's views and biases to enter into the finished product; this was precisely the relationship found by Dougal, Engelberg, Garcia and Parsons (2012). The authors made use of the AOTM column and the DJIA, spanning a sample period of close to four decades. The authors were also cautious about making a distinction between a reflective and a causal role for financial media; this required exogenous variation in news content or reporting uncorrelated with underlying events. The methodology employed addressed this concern as in the sample period, columnists rotated frequently according to regular schedules and differed in their writing styles. The results showed that in the short-term, returns on the DJIA can be predicted using only the author of the AOTM column – that is a causal relationship was found. This result is surprising because at any point in time, individual columnists are unlikely to possess information relevant to the market as a whole and thus any predictability related to the specific authors was interpreted to arise from their own sentiment. Two inferences may be drawn from the results of this research; firstly, financial journalists have the potential to influence investor behaviour in the short-term and secondly, the interpretation of public news is important as the strongest effects were found when journalists wrote about significant market movements.

Insight into the German financial market is provided by Singer, Laser and Dreher (2013) who develop a new investor sentiment measure for the German market using published stock recommendations (by professional analysts) in both print and online media. The first data set, sourced from print media, provides selected analyst forecasts published in *Frankfurter Allgemeine Zeitung*, a high-profile German newspaper; the second data set, sourced from online media, uses stock recommendations from *dpa-AFX Wirtschaftsnachrichten GmbH*, a leading financial news agency in a specific region. Both sources in question categorise recommendations as buy, sell, and hold which allows a traditional bull-bear spread to be applied. Since the stock recommendations are made by professional analysts, it is assumed that this will be a measure of professional investor sentiment. The performance of the German financial market is measured by the DAX index. Using vector autoregressions, weekly sentiment was found to have no near-term forecasting power on returns. However, sentiment was found to be a strong predictor of itself and that past stock movements drive sentiment. Unlike the evidence from Solt and Statman (1988) and Brown and Cliff (2004) who find that sentiment follows a positive feedback process, the evidence from German indicates the opposite. In this instance, professional analysts express optimism in their printed stock recommendations when previous market returns were negative. Weak evidence for the positive feedback process was found in the case of online media sentiment, however this relationship was found not to be Granger causal. In the case of print media, there was strong and causal evidence demonstrating that professional analysts follow reversals. The authors postulate that their results are in line with the "bargain shopper hypothesis" outlined by Brown and Cliff (2004); when analysts see shares becoming a bargain (indicated by a negative return) they see a buying opportunity and thus become optimistic.

Until recently, media effects were examined by utilising conventional media such as newspaper and magazine articles. However, the Internet has enabled an increasing amount of user generated information through the explosion of social media networks. This is not only seen as a primary source of information for both consumers and businesses alike, but also provides a further mechanism with which to understand and measure investor sentiment (Yu, Duan, & Cao, 2013). Social media provides a platform for creating, sharing and exchanging user generated information; as a result there are many people sharing their opinions and experiences and hence forms an aggregation of personal wisdom and different opinions. Although these aggregations have limitations with viewpoints continually changing, if extracted and analysed appropriately the data can provide a large volume of valuable insight (Yu & Kak, 2012). Moreover, a large part of the existing literature focuses on role of conventional media outlets where the investor is the recipient of information; social media, however, enables investors to not only consume but also generate information (Chen, De, Hu, & Hwang, 2011). This provides a much richer data source for mining the opinions of investors.

The recent years have seen tremendous growth in the user bases on various social media platforms, and hence have caused a fundamental shift in public disclosure and communication in society. Previously, a major barrier for someone seeking to distribute information throughout a community was the cost of technical infrastructure required to reach a large enough group of people. However, with increased Internet penetration the bottleneck has been removed and hence the mainstream adoption of social media has changed the dynamics of information diffusion (Stieglitz & Dang-Xuan, 2013). Research into the role of social media in information diffusion has been conducted with results emphasising the strength of its role. Bakshy, Marlow, Rosenn and Adamic (2012) evaluated how much exposure to a unique URL[7] on one's Facebook News Feed would increase an individual's propensity to share that URL, beyond what would be expected through Facebook friends. They found that those individuals who are exposed are significantly more likely to spread information and do so much sooner than those who have not been exposed. Moreover, emotions appear to play a critical role in information dissemination as was found by Stieglitz and Dang-Xuan (2013). In this case, Twitter, the micro-blogging social media platform, was used as the ability to 'retweet' is seen as a powerful mechanism of information sharing. Two data sets – one with emotionally charged tweets and one with emotionally neutral tweets – were used, amounting to 165 000 tweets in total. The authors found that the emotionally charged tweets tend to be retweeted more often and quicker compared to the neutral ones. The wealth of data on social media platforms as well as its role in information diffusion are important determinants in studying its effects.

Seeking Alpha (SA), a personal finance social media website, is a platform for investors to provide insight and analysis garnered from their own personal experiences. Websites such as SA have become increasingly popular due to the rise in the trend of peer-based advice; SA is the most popular of these websites and hence was chosen for opinion mining in a study conducted by Chen, De, Hu and Hwang (2011). The authors sought to investigate how the views expressed on SA affect investor trading and hence stock prices of over 3 000 companies over a 4 year period. A strong link was uncovered between the views expressed on SA and contemporaneous and subsequent stock returns, even after controlling for the effect of traditional advice sources. This relationship was found to be stronger for articles that receive the most attention and companies whose shareholders are mainly retail investors. The outcome of their research highlights the growing role, not only of peer-based advice, but also of social media in financial markets.

[7] A URL is a Uniform Resource Locator which refers to the global address of documents and other resources on the World Wide Web.

Similar results were uncovered when Yu, Duan and Cao (2013) investigated the effects of social and conventional media on short-term firm stock performance. They employed a much broader media dataset than previous studies by using daily media content from social media outlets such as blogs, forums and Twitter; and conventional media sources such as newspaper and magazine articles. Additionally, the company dataset was also much broader as they examined 824 companies, spanning 6 industries including pharmaceuticals, retail, software, savings institutions, health care and accommodation. The sentiment index was created by employing the same algorithm used by Antweiler and Frank (2004) – Naïve Bayes. This algorithm was used to detect which text segments contained sentiment signals, followed by determining the polarity and strength of that sentiment. The polarity and strength were measured on a scale from -1 to 1; a score of 1 (-1) means that the media source has a positive (negative) view for the company. Through their analysis, the authors showed that overall social media sentiment has a stronger impact on firm stock performance than conventional media, while social media and conventional media have a strong interaction effect on firm stock performance. These results highlight two important inferences for further research. Firstly, it is important to examine both social and conventional media when considering sentiment as the evidence has shown that both indicators have an impact on firm stock performance. Secondly, there may be an industry effect at work as evidence of a relationship was found spanning across 6 industries, however when Internet service companies (Tumarkin & Whitelaw, 2001) and tech sector companies (Das & Chen, 2007) were studied there was very little evidence found to support this relationship.

Twitter provides up to the minute information and is a novel way of capturing investor opinion. It is for this reason that Zhang, Fuehres and Gloor (2009) used this platform to gauge investors' emotions when investigating whether stock market indices could be predicted by analysing Twitter posts. They made use of the Dow Jones, S&P 500 and NASDAQ indices and collected Twitter feeds for a 6 month period in 2009. Due to the nature of Twitter, short posts with a generally simple meaning where one or two words are able to capture the topic, the authors used mood words such as “fear”, “hope”, and “worry” as emotional tags of a tweet. The emotion expressed on a daily basis was calculated as simply the number of tweets with each specific mood word. Although only preliminary results were presented, it was found that when investors are negatively emotionally charged, expressing large amounts of fear and hope, the Dow Jones Index declines the following day. Similarly, when investors were positively emotionally charged, the Dow Jones Index increases the following day.

Twitter was once again used as a data source when Sprenger and Welpe (2010) sought to answer two questions: 1) Whether and to what extent the information content of Twitter posts reflects financial market developments and 2) Whether Twitter posts provide an efficient mechanism to weigh and aggregate information. In accordance with Antweiler and Frank (2004) the Naïve Bayesian classification method was employed to classify messages into a buy, hold or sell signal. Financial data was collected for the S&P100, which encompasses shares that trade on the NASDAQ and NYSE. Accordingly Twitter messages were aligned with US trading hours (9:30 to 16:00) by assigning messages posted after 16:00 to the next trading day. The results show that increased bullishness of Twitter posts is associated with higher returns; both a contemporaneous and lagged relationship was found between bullishness and abnormal returns. Twitter users were found to follow a contrarian strategy as "buy" signals were accompanied and followed by abnormal returns, far exceeding the assumed level of transaction costs. Conversely, "sell" signals were found to have no predictive power for returns. The information content of Twitter posts was found to be incorporated into market prices quickly; however transaction costs make it difficult to exploit the market inefficiency. An interesting feature of Twitter is the ability to gauge reputation; in this instance, the authors found that users who provide above average investment advice are given credit and greater share of voice through higher levels of re-tweets and followers.

Much of the existing research relating to social mood and its effect on security prices tends to focus on the sentiment of individuals and how this affects their decision making; Bollen, Mao and Zeng (2011) sought to determine if this phenomenon applied to large societies. Their primary research question was "Can societies experience mood states that affect their collective decision making?" The measurements of collective mood were derived from large scale Twitter feeds; this was then tested against the DJIA to ascertain correlation over time. Two tools are used to measure variations in public mood: OpinionFinder and Google-Profile of Mood States (GPOMS). OpinionFinder analyses the text content of tweets recorded on a given day to provide a positive versus negative daily time series of public mood. GPOMS also analyses the text content of tweets to generate a six dimensional daily time series of public mood (these dimensions include Calm, Alert, Sure, Vital, Kind and Happy); this provides a more detailed view of changes in the public along a variety of different mood dimensions. First and foremost, changes in the state of public mood state can be tracked from the content of large scale Twitter feeds through simple text processing techniques. This once again validated the use of Twitter as a tool for measuring both individual and collective sentiment. Among the observed mood dimensions only some were found to be Granger causative of the DJIA; changes of the public mood along these mood dimensions match shifts in the DJIA values 3 or 4 days later. This effect was not observed for OpinionFinder's general assessment of public mood, but rather for the GPOMS dimension labelled "Calm". The calmness of the public is thus predictive of the DJIA as opposed to general levels of sentiment. Overall, the prediction accuracy of standard financial market predictions models can be significantly improved when certain mood dimensions are included. The outcomes of this research have important implications for sentiment tracking tools, specifically surveys which involve individuals evaluating the extent to which they experience happiness, satisfaction or dissatisfaction with life. These surveys tend to be expensive and time-consuming and may not allow the measurement of public mood dimensions that are relevant to assess socio-economic indicators. Public mood analysis using Twitter feeds provides an automatic, free, fast and large scale addition to sentiment tracking which can be optimised to measure various dimensions of public mood state.

The computer hardware and software industries were put under scrutiny when Luo, Zhang and Duan (2012) sought to determine if there is a predictive relationship between social media and firm equity value and if this social media effect is stronger than a conventional media effect. The reason for choosing these two industries is the theory that the customers of these companies are more likely to participate in and be influenced by digital media and hence these industries need to leverage social media. Their results indicate that social media, in this particular case blog posts, are a leading indicator of firm equity value and have stronger predictive power than conventional media metrics. As a secondary objective, they measured the level of investor attention using Google searches and web traffic and found that these metrics have only moderate predictive power. The implication of these results is that social media, rather than being viewed as cost, should be viewed as an important tool to influence firm equity value and hence investment in social media and information technology is justifiable.

Chen, De, Hu and Hwang (2014) once again made use of Seeking Alpha to investigate the extent to which opinions transmitted through social media predict future stock returns and earnings surprises. In addition to the textual analysis conducted on articles published on the website, the authors analysed the commentary written in response to the articles. Articles posted between 2005 and 2012 were downloaded from the SA website; the authors opted to focus on single-ticker articles whereby only one stock was discussed, this amounted to just over 97 000 articles. The commentary for each of the articles was also downloaded; in this instance, the authors focused on commentary that was written within the first two days of the article being published. Authors’ opinions were extracted by assuming that the frequency of negative words used in an article captures the tone of the report (Tetlock, 2007; Tetlock, Saar-Tsechansky, & Macskassy, 2008). Articles were gathered from the Dow Jones News Service in order to determine if SA articles and commentary have an effect above and beyond news released through traditional media outlets; these articles were used to construct a measure of information revelation. It was found that the opinions revealed through SA articles and commentary strongly predicts future stock returns and earnings surprises. This relationship was found to hold even after controlling for the effect of traditional advice sources such as newspaper articles. This highlights the usefulness and value in a peer-based advice system.

Unlike a number of previous studies, Karabulut (2013) used the social networking platform Facebook to determine its predictive power of movements on the US stock market over a 3 year period. The sentiment variable, the GNH index, is compiled by determining the sentiment from the content of Facebook status updates. GNH is calculated using the word-count methodology in which Facebook measures a status update’s positivity (negativity) according to relative frequency of with which positive (negative) emotion words are used. The results showed that the GNH has the ability to predict statistically significant and economically meaningful changes in aggregate market returns. Moreover, the positive influence of the GNH on market returns is temporary and completely reverses during the following trading weeks. These results are not only consistent with noise trader models (De Long, Shleifer, Summers, & Waldmann, 1990) but the evidence of an initial increase and subsequent return reversal supports the hypothesis that the GNH serves as a proxy for investor sentiment.

It is clear that investors are making use of social media platforms to voice opinions and share their own personal experiences; this indicates that investors are allocating attention to a particular topic or stock. Gaining an understanding of investor attention and its effects is as much of a challenge as trying to quantify and explain the effect of investor sentiment. The primary reason for this is that many indirect proxies are used to measure investor attention, as is the case when trying to measure investor sentiment. The proxies for investor attention include extreme returns, trading volumes, news and headlines, advertising expense and prime limits (Da, Engelberg, & Gao, 2011). In order to gain a thorough understanding of investor attention, which can be used as a proxy for investor sentiment Da, Engelberg and Gao (2011) developed a new and direct measure of investor attention by the Search Volume Index (SVI) made available by Google Trends. The authors opted to focus on the largest 3 000 companies that comprise the Russell 3000 index in the United States. In order to identify a stock on a Google search, the stock ticker itself was used as the search word as it implies that an investor searching for the ticker name is interested in financial information concerning the company. Their results showed that an increase in SVI for any Russell 3000 stock predicts higher stock prices in the next 2 weeks with an eventual price reversal occurring within a year. The use of search volume is a key development in understanding investor attention and sentiment as it provides an objective way to collect and quantify investors' interests.

Joseph, Wintoki and Zhang (2011) conducted research similar to that which was undertaken by Da, Engelberg and Gao (2011). Using data from Google Trends and choosing to focus solely on financial shares, the authors tested the predictive ability of search volumes of stock tickers on abnormal stock returns and trading volumes, measured from the S&P 500. The motivation for the use of tickers and not the actual company is similar to that outlined by Da, Engelberg and Gao (2011); an investor searching for a ticker name is more likely to be interested in financial information concerning the company than someone merely searching for the company name which could yield information far removed from an investment decision. The search was narrowed to financial tickers as the effort required to process the results of a ticker query is worthwhile only for someone seriously considering an investment decision. On a weekly basis, the sample of S&P 500 firms was divided into five quintiles based on the search intensity the previous week. The subsequent stock returns and trading volumes across all quintiles is examined to determine the predictive power of search intensity. Over a weekly horizon, online search intensity reliably predicted abnormal stock returns as well as trading volume. Moreover, the sensitivity of returns to search intensity is positively related to how easily a stock can be arbitraged. Specifically, the sensitivity of returns to search intensity is lowest (highest) for easy-to-arbitrage (difficult-to-arbitrage), low (high) volatility shares. It is important to note that this finding is validated by Baker and Wurgler (2007), who used a selection of market variables to measure investor sentiment. The fact that this relationship was found when the choice of market measure (S&P 500 versus stock price returns) and measure of investor sentiment (online search volumes vs. market variables) were different points to the robustness of the relationship. The outcome of this research, taken together with Da, Engelberg and Gao (2011) and Baker and Wurgler (2007) provide a consistent story: the intensity of search for ticker symbols serves as a valid proxy for investor sentiment which is useful for forecasting stock returns and volume. Moreover, this measure is able to provide a cross-sectional analysis which provides further insight.

Rao and Srivastava (2012) make use of Twitter to investigate the relationship between tweets and financial market metrics, such as stock prices. The analysis covered more than 4 million tweets between 2010 and 2011 for the DJIA, NASDAQ-100 and 13 other large capitalisation technology shares. The tweets were classified as positive or negative using the Naïve Bayes algorithm and considered characteristics such as bullishness, message volume and agreement. The first set of results came from testing the correlation results between Twitter sentiment and stock prices for the different companies and indices. A very strong correlation was found to exist between these two variables, the highest being 0.88. Granger-causality tests were then employed to ascertain the causal relationship between the two variables, which also demonstrates whether a leading or lagging relationship exists. The movement in stock prices and indices was found to be greatly affected by Twitter discussions, however only in the short-term. This implies that Twitter sentiment is seen to follow the leading indicator property. Finally, in order to determine the predictive power of the Twitter sentiment an Expert Model Mining System (EMMS) was implemented. The results were somewhat mixed in this regard, with Twitter sentiment only demonstrating predictive power for the DJIA and none of the other shares or indices. These results imply that both negative and positive dimensions of public mood carry strong cause-effects relationships with price movements in individual shares and a number of indices.

Evangelopoulos, Magro and Sidorova (2012) explored a framework for understanding the role social media sites play in informing clients at an individual message (micro) and aggregate (macro) levels. According to the authors, social media sites are seen to play a dual informing role, "as a platform for individual informing actions and as a macro informer, informing its clients about their user community and, by extension, by the society at large" (Evangelopoulos, Magro, & Sidorva, 2012, p. 250). In order to validate this framework the authors examined if an aggregate of Twitter messages can be used as a predictor of future stock prices of 18 Fortune 500 companies. Using latent semantic analysis, semantic and conceptual content is extracted from tweets in the form of key themes. Thereafter, a regression model is fit using tweet volume and tweet topic strength to predict the variability in security prices beyond what can be explained by fluctuations in the stock market. Their regression predicted 8.3% of the variability in security prices that is unexplained by normal security market fluctuations; implying that Twitter is an effective stock market predictor and a leading indicator of stock marker performance. At a macro level, Twitter content can be analysed using text mining methodologies which can inform potential unintended clients about future economic activity, such as stock market performance.

An innovative approach was taken by Da, Engelberg and Gao (2015) who constructed an index based on the volume of search queries and then quantified the effects of this index on asset prices and fund flows. Their objective was to build a list of search terms that reveal sentiment towards economic conditions; this list of words includes “bankruptcy”, “unemployment”, “crisis”, “inflation”, “recession” and “security”; as such their index was named the Financial and Economic Attitudes Revealed by Search (FEARS). In total they compiled a “primitive” list of 149 words; the next step was to understand how these words were searched in Google. This was done by inputting each primitive word into Google Trends and then extracting the related terms for a specific term. At the end of this their primitive list of 149 words generated 1 245 terms after duplicates were removed. Their remaining data sets were four highly liquid exchange traded funds as well as Treasury portfolio returns for the 10 year constant maturity Treasury file. When FEARS was quantified against asset prices it was found that although increases in FEARS correspond with low market level returns today, they predict high returns over the next few days – the FEARS index predicts return reversals. This effect was found to be stronger for shares favoured by sentiment investors and those that are difficult to arbitrage. Through their analysis regarding mutual fund flows, it was found that increases in FEARS triggered daily mutual fund flows out of equity funds and into bond funds. This evidence is broadly consistent with the “noise trading” theory outlined by De Long, Shleifer, Summers and Waldmann (1990).

The FEARS index, as a measure of investor sentiment, has been used as a measure if investor sentiment; however the results have been somewhat mixed:

- Lien and Hauge (2012) sought to understand the role of fear and ambiguity in the Norwegian financial market by constructing a volatility index (NVIX) and a specific Norwegian FEARS index (NFEARS). NFEARS was found to have very little explanatory power when tested against their market index. Instead, NVIX was found to capture fear and ambiguity in the Norwegian market.
- Chen, Han and Pan (2014) examine sentiment risk as a determinant of hedge fund returns. Sentiment risk is captured through three different measures: the Baker and Wurgler (2006) index, the MCSI, and the FEARS index. The central finding was that hedge fund exposure to sentiment risk is significantly and positively related to their

expected returns. This outcome was found to be robust across all three measures of sentiment risk and therefore it can be concluded that sentiment risk is priced into the cross-section of hedge fund returns.

The viability of Google Trends and social media platform StockTwits as stock market predictors was studied by Loughlin and Harnisch (2013). There exists both a bullish and bearish StockTwits index; messages were compiled for a 3 month period with the total amounting to 19 000 messages. The Google Trends data was compiled and aggregated directly from the website; the index includes search terms relating to a particular company such as the company name and its products and/or services. This particular chose to focus on Apple, Google, Microsoft and Facebook with the aim of modelling the rapid movement in technology shares using fast estimators such as StockTwits and Google Trends. Unlike Da, Engelberg and Gao (2011), the authors reported that Google Trends was not a significant predictor of stock returns. It is possible that this outcome was due to the study only covering four technology shares over a 3 month period. Conversely, StockTwits was found to have significant predictive power in predicting returns for Apple, Google and Microsoft. Moreover, when the StockTwits data was lagged, the bull and bear indices were significant in predicting Apple and Microsoft stock returns. This outcome suggests that StockTwits is a significant leading predictor of stock returns.

Extracting investor information from newspaper and magazine articles is a relatively new concept and has had quite a slow uptake; however, once the benefits of the initial studies were realised, the popularity of this methodology has increased. Much of the data is extracted through textual analysis and positive results have been observed. Using a variety of newspaper and magazine sources as well as numerous methodologies, investor sentiment measures were constructed which were found to have a significant relationship with stock price performance. The use of media as a data source evolved even further with the advent of social media platforms such as Facebook and Twitter. Once again, academics saw these platforms as rich sources of data as it extracted insight straight from investor opinions. Investor sentiment indices were constructed using the data from these social media platforms and their effects tested on stock price performance. Positive results were uncovered through a significant relationship found between the two variables. News and social media has become an important tool in measuring investor sentiment, mainly due to the quality of data it produces.

2.3.4.4 Internet Message Boards

In the United States, Tumarkin and Whitelaw (2001) sought to investigate the relationship between Internet message board activity – a proxy for investor attention – and abnormal stock returns and trading volumes. They made use of the Internet forum Raging Bull (RB) and were able to create a quantitative measure of investor opinions on a daily basis over a 12 month period. Furthermore, the focused purely on 73 Internet service companies as it was hypothesised that they, as a group, would be most affected by the information contained in these forums. Although this study was supported by a logical rationale and a strong methodology, the authors found no statistically significant association between the postings on RB and companies' stock returns. The results beg the question, is there information content present in stock message boards?

Antweiler and Frank (2004) sought to answer this question by making use of the RB and Yahoo! Finance (YF) message boards. The sample of stocks was a combination of 45 stocks that together made up the DJIA and the Dow Jones Internet Commerce Index. The Naïve Bayes algorithm was employed to assess the content of each stock message. They found that there is useful information present on the stock message boards, with the magnitude of these effects being quite large relative to other features of the stock market that have attracted attention. They were able to conclude that although a statistically significant relationship between investor opinion and stock returns exists, it is economically small due to plausible transaction costs.

Das and Chen (2007) studied 24 tech sector stocks that were present on the Morgan Stanley High-Tech Index. The purpose of this exercise was to focus on the tech sector and to leverage the large amount of activity on their message boards. Their sentiment index was created by first, extracting articles on these message boards over a 2 month period and then using algorithms to assess each message and determine its sentiment. They then proceeded to create an index from their chosen stocks and a link from sentiment to the index was found at an aggregate level. Upon delving deeper, they found no strong relationship from sentiment to stock prices on average across the individual stocks.

Sehgal and Song (2007) identified stock message boards as a source of rich financial information due to the popularity in exchanging ideas and information. Through the use of various algorithms, the authors scanned financial message boards and extracted the sentiment expressed by individual authors. They used this sentiment to create and index and tested whether this index could predict movements in financial markets. Over a 6 month period and using the Yahoo! Finance message board, over 26 000 messages were collected for 52 popular shares that trade on the NYSE or NASDAQ, covering many different industries. Apart from posting messages, Yahoo! Finance users can express the sentiment of their posts as “Strong Buy”, “Buy”, “Hold”, “Sell” or “Strong Sell”. The sentiment index was modelled according to a Markov process and was created using Naïve Bayes. An interesting concept, unique to this research, was the concept of trust. The authors were well aware of the fact that web financial information is not always reliable and hence crated a measure of trustworthiness called TrustValue. This measure improved the accuracy of the prediction by filtering irrelevant or noisy sentiment. The results showed that sentiment and stock value are closely related and web sentiment is an effective and accurate predictor of stock behaviour.

The somewhat mixed results found in the above studies could be attributed to either the small sample sizes employed, or the infancy of social media at the time the studies were conducted, in which case the initial inconsistencies are expected. The results of research conducted in later years yielded more consistent results indicating an evolution in this new area of research.

Further support for the prediction hypothesis was provided by Oh and Sheng (2011) who made use of the Yahoo! Finance message board as well as Stocktwits, a variant platform of Twitter that aggregates only stock-related postings. Over the course of 3 months, the authors collected over 200 000 stock micro blog posts for stocks that are listed on both the NASDAQ and NYSE. Each micro blog post was labelled as bullish, bearish or neutral sentiment. Sentiment was aggregated using the bullishness index introduced by Antweiler and Frank (2004). The outcome of the study reiterated the existing evidence that stock discussions are not noise and that they do in fact have predictive power, consistent with Antweiler and Frank (2004). Furthermore, their effect on economic outcomes is real, substantial and of great value to individual and institutional investors seeking an effective way to predict stock returns.

A Chinese perspective was offered by Wang (2012) who took a cross-sectional view and tested the hypothesis that the length of postings on Internet message boards is a determinant of financial market performance. This particular study considered 2.85 million postings (ignoring the comments section) of 58 firms listed on the HS300 index in China. EastMoney.com was used as the source for message postings as it has become the most influential financial information service provider in China. Submission times were used to classify postings, any post before 15:00 was classified as today’s postings, while anything after 15:00 was classified as tomorrow's post. It follows that anything posted before the Chinese stock exchange closed would influence that specific days' sentiment; similarly, anything that was posted after the stock market closed would only have an effect on the next day's sentiment. Overall, it was found that the number of postings on stock discussion boards often leads to a slight decline of stock return and an increase in volatility. After dividing the postings into five different groups in terms of text length, it was found that postings with different words play different roles. The magnitude of correlation between postings and stock returns varies by the number of words – postings with fewer words are emotion-expressed and were found to have a positive correlation with returns; longer posts are too rational to bring information to affect the stock market and a negative correlation with returns was found; finally postings with a large number of words were part of financial reports or official news which convey useful information to the market and hence a positive correlation with returns was found.

Most recently, Kim and Kim (2014) examined the relation between investor sentiment and its effect on future stock returns by constructing a sentiment index using pots from Yahoo! Finance message boards. This study's approach is similar to work conducted by Tumarkin and Whitelaw (2001), Antweiler and Frank (2004) and Das and Chen (2007) however the authors opted to expand the time period as well as the variety of stocks in terms of firm size and industry. Over their six year sample period, the authors analysed 91 firms with the most active Yahoo! Finance message boards and opted to perform their analyses over several different time horizons. Most importantly, new functionality on the Yahoo! Finance message board, post 2004, allowed investors to reveal their sentiment using five categories: "Strong Buy", "Buy", "Hold", "Sell" and "Strong Sell". This provides a more robust way to examine the relation between investor sentiment and stock returns. Despite a more thorough methodology than its predecessors, the evidence showed no evidence in intertemporal analyses that investor sentiment forecasts future stock returns, both at an aggregate and individual firm level.

Internet message boards provide an advantage over and above that which is provided by news and social media: there are dedicated internet message boards for specific topics e.g. finance and those who participate in these discussions are assumed to be informed to a certain extent. Therefore extracting information from Internet message boards is simpler, in that a specific finance board can be targeted, and the data extracted is assumed to be from informed investors. Data from numerous finance Internet message boards was used to construct a measure of investor sentiment; this was then tested against stock price performance. The outcome showed that the information content on Internet message boards can be used as a measure of investor sentiment and a significant relationship between the two variables was uncovered. Internet message boards are now viewed as an important data source, not just for measuring investor sentiment but for gathering data on a number of topics.

2.3.5 The Asymmetric Effects of Good and Bad News

An important part of analysing investor sentiment, particularly textual analysis, is understanding the difference between the effects that good and bad news have on financial markets. Essentially, individuals have different reactions to good news and bad news, hence affecting their decision making and ultimately their actions. Thus, when it comes to analysing investor sentiment through textual analysis, it implies that words with positive connotations and those with negative connotations will have different impacts on investor sentiment.

The asymmetry between positive and negative is a phenomenon largely grounded in psychology theory, which has subsequently been applied to various domains. The positive-negative asymmetry effect has repeatedly been confirmed, with the outcome of research indicating that negative is significantly stronger than positive (Anderson, 1965; Peeters & Czapinski, 1990). It should be heeded though that this does boil down to a game of numbers; it is not always the case that negative triumphs over positive; rather positive events may prevail over negative ones due to the force of numbers. A number of positive events can overcome the effects of a single negative event; however, when there are equal measures of positive and negative the effects of the negative events tend to outweigh those of the positive events (Baumeister, Bratslavsky, Finkenauer, & Vohs, 2001).

In terms of offering an explanation as to why negative is stronger than positive, much of theory points to the fact that it is evolutionarily adaptive for negative to be stronger than positive. For example, a person who ignores the possibility of a positive outcome may later experience regret, but nothing directly terrible is likely to result. Conversely, a person who ignores danger could end up in a terrible outcome. Evolution dictates that survival requires urgent attention to possible negative outcomes, but is less urgent when it comes to positive outcomes. Therefore, it may be concluded that it is adaptive to be psychologically designed to respond to the negatives more than the positives (Baumeister, Bratslavsky, Finkenauer, & Vohs, 2001). It is this positive-negative asymmetry that has then been applied to various domains, such as financial markets.

One of the earliest examples of stock markets reacting asymmetrically to positive and negative elements is De Bondt and Thaler's (1985) work on the overreaction hypothesis. Monthly return data for NYSE shares between the period January 1926 and December 1982 is used; focus is put on shares that have experienced either extreme capital gains or extreme losses over periods of up to five years. In other words, the 'winner' and 'loser' portfolios are formed conditional upon past excess returns. The core finding of this work was the presence of overreaction on the stock market; however this effect was found to be asymmetric in that overreaction is much larger for the 'loser' portfolio than for the 'winner' portfolio.

Positive-negative asymmetry also has a place in investigating momentum strategies, as was uncovered by Hong, Lim and Stein (1998). An information-diffusion model is used to understand the medium-term momentum in stock returns that was originally identified by Jegadeesh and Titman (1993). Two primary factors were considered in their explanation: size and analyst coverage. Analyst coverage, however, is the only factor available to be influenced either negatively or positively. In the results it was shown that momentum strategies work well for shares that have low analyst coverage, with this effect being more pronounced for shares that were classified as past losers than shares who were past winners. This outcome is consistent with the hypothesis that firm-specific information, particularly negative information, diffuses across the investing public with a significant asymmetric effect.

Giner and Rees (2003) investigated whether accounting systems recognise bad news more promptly than good news, using changes in the stock price as a proxy for news. Their analysis covered France, Germany, and the UK between 1990 and 1998. The rationale for choosing these particular countries is that these are the originators of three distinct legal traditions; with previous studies having indicated that asymmetric recognition is sensitive to legal background and history. The results showed that in all three countries the contemporaneous association between earnings and returns is much stronger for bad news (negative stock price changes) than for good news. This implies that bad news is recognised more quickly in the accounting systems of these countries than good news is.

Soroka (2006) investigated possible asymmetries in mass media responsiveness to positive and negative economic shifts in the UK using time series data of media and public opinion. Strong evidence of asymmetry was found as public responses to negative economic information were found to be much greater than public responses to positive economic information. The same trend was observed in mass media content which served to enhance the asymmetry in public responsiveness. This serves to confirm the presence of the positive-negative asymmetry effect in the UK media.

Support for Soroka's (2006) outcome in the UK was provided by Ju (2008) who investigated whether a negatively biased news coverage of the economy was present in South Korea, and whether this affected public perception. The pattern found was similar to Soroka's (2006), as negative economic news tended to appear more frequently on the front pages of two different Korean newspapers than positive news, regardless of the state of the economy. Surprisingly, even when the economy went through a period of improvement, no positive economic news appeared on the front pages. Regression testing was employed and the negative bias was observed there as well: negative news coverage was found to be associated with the real economy while positive news coverage was reduced even when the economy was improving. These results support the notion that news media fulfils people's demand for threat-detecting news, consistent with the evolutionary explanation provided by Baumeister, Bratslavsky, Finkenauer and Vohs (2001).

The presence of the positive-negative asymmetric effect implies that when studying any given economy, differentiating between positive and negative news could potentially lead to richer insights. This was the focus of the study conducted by Knif, Kolari and Pynnönen (2008) that used CPI and PPI to test the effect of good and bad inflation news announcements on US stock market returns. Their results indicated that positive and negative inflation shocks can have a relatively large cumulative effect on aggregate stock returns depending on the economic state as well as investors' perceptions of these inflation announcements. Moreover, when inflation announcements are viewed by investors to be negative, the impact on stock returns is much greater than in the case of announcements being viewed as positive. Apart from the presence of the positive-negative asymmetric effect, a key point to be drawn from this study is that by not differentiating between positive and negative elements, there exists a risk that any potential effects on financial markets may be diluted.

Evidence of the positive-negative asymmetry effect appears to be present in a number of areas in the finance realm – the bond market is no different. Beber and Brandt (2010) examine how US Treasury bond returns and their volatility react to good and bad macroeconomic news in economic expansions and recessions. Strong evidence of asymmetry was uncovered as the information content of the announcements was found to be the most important for bond returns when it contained bad news for the bond market in expansions, and to a lesser extent, when it contained good news for the bond market in contractions.

Much of the existing literature pertains to the fact that the positive-negative asymmetry effect is present in the public arena; however, there is evidence to show that asymmetry exists at a much more granular level as well. One such example is in the construction of the FEARS index of Da, Engelberg, and Gao (2015), which is constructed using search words and data from Google Trends. In this instance, a backward run regression was used to determine which search words, of the complete list, would have the largest impact on financial market returns. The results indicated that those words with negative connotations had a much larger impact on returns than words that were positive in nature. Thus, the 'negative' words were the ones included in the construction of the index which was subsequently tested against asset returns and a volatility index with positive empirical results.

Apart from the application of the positive-negative asymmetry effect in the financial context, there is evidence that suggests this effect is present in social discrimination studies (Mummendey & Otten, 1998; Mummendey, Otten, Berger , & Kessler, 2000), the impact of reputation on e-commerce companies (Standifird, 2001), website attribute performance and satisfaction (Cheung & Lee, 2005), voting behaviour (Kernell, 1977; Arangones, 1997), and the trustworthiness of studies regarding health risks (Siegrist & Cvetkovich, 2001).

Explanations of the positive-negative asymmetry effect from the psychology viewpoint and thereafter the application to financial markets – as well as other realms of research – indicates that individuals have a stronger response to possible negative outcomes or bad news as opposed to possible positive outcomes or good news. If this is related back to investor sentiment and textual analysis, it would be expected that negative search words would have a much larger impact on investor sentiment and subsequently financial returns than positive search words would have.

2.3.6 Summary

Behavioural finance studies the influence psychology has on financial practitioners and their behaviour; essentially, is the intersection of psychology, sociology and conventional finance theory. Where conventional finance theory assumes that capital market participants are rational consumers, behavioural finance allows for irrationality and explores how the world can be explained from a psychological and sociological point of view. Investor sentiment, specifically, focuses on how an investors' emotions and feeling might influence their financial decision making which, ultimately, has an impact on financial markets. Investor sentiment has gained popularity in its ability to explain aspects of both investment theory and returns. Specifically, investor sentiment has made an appearance in explaining noise trader theory, been used to modify the CAPM and used in the APT model to better explain returns. In terms of investor sentiment measurement, it can be quantified in multiple ways: using survey data, proxied by market variables, through news and social media and finally using Internet message boards. In explaining returns, investor sentiment has been able to do so across all these mediums of measurement. Finally, an important aspect of investor sentiment and its measurement is the asymmetric effect individuals experience between positive and negative information. Individuals tend to react stronger to negative information than positive information; this implies that the effect of negative news on the stock market could be much greater than the effect of positive news. This effects becomes especially important to understand when conducting textual analysis to capture investor sentiment.

2.4 Literature Review Summary

The literature review has demonstrated that investor sentiment is not only a critical component of behavioural finance but also plays a large role in explaining other aspects of finance theory.

A fundamental building block in asset pricing is the CAPM which asserts that asset prices and their associated returns are a factor of market risk, and market risk alone. The model has come under criticism due to the assumptions underpinning the model, as they are viewed as restrictive and unrealistic when applied to the real world. Augmentations to the original CAPM have been done throughout the years; it has been developed under an international lens and has been expanded to include explanatory factors other than market risk. The APT was developed to address a number of the empirical challenges faced by the CAPM; it was developed as a framework for explaining asset returns. It is a more flexible model in nature as it allows for a multitude of factors to be used in explaining asset returns. Much of APT's empirical research focuses on which factors to include as well as the optimal number of factors which can be used to fully explain asset returns. One of the developments in APT literature is the development of a macroeconomic APT, which has become the focus of this study. The nature of a macroeconomic model implies that different macroeconomic variables can be used to explain market returns in different market – what might explain market returns in one country does not necessarily hold as much explanatory power in a different country. That being said, the flexibility of the APT implies that a degree of creativity can be applied when seeking to explain asset returns. This lends itself to the inclusion of a behavioural finance concept, such as investor sentiment, to be included as an explanatory factor.

The role that investors' emotions play in financial markets has been used as an explanation in various other aspects of finance – in both investment and corporate finance theory. Investor sentiment has also been used in various instances to explain market returns, with various measurement options being applied in different contexts. The measurement has evolved quite substantially over the years; surveys are the only direct measure of sentiment and have been used extensively to understand the role investor sentiment plays in explaining returns. Measurement of sentiment has also extended to include proxies, such as market variables, and sentiment indices developed from news, social media and Internet discussion boards. Regardless of the measurement, however, investor sentiment has demonstrated itself as a critical component in understanding and explaining stock returns.

Overall, investor sentiment plays a significant role in explaining various components of finance as well as market returns; the macroeconomic APT with an investor sentiment factor now presents an opportunity for investor sentiment to explain asset pricing.

3 Data and Methodology

The choice of sample period is dependent on the availability of the required data sources. Due to the international nature of this study as well as the data sources used, unfortunately different sample periods will be used for the different countries. Although this limits the study in terms of comparability between countries, it ensures that the study remains statistically robust. As such, the various sample periods of each country are outlined below:

- Brazil, Russia, India, South Africa, Germany, US: February 2010 to June 2015 (65 monthly observations).
- UK: March 2010 to June 2015 (64 monthly observations).
- China, Japan: January 2012 to June 2015 (42 monthly observations).

3.1 Data

3.1.1 Choice of Countries

In addition to studying the South African market, the remaining BRICS countries will be studied; this includes Brazil, Russia, India and China. For the purposes of this study, the BRICS nations will be grouped as the developing nations.

In terms of the choice for the developed markets, the G7 countries were used as a starting point. The G7, as ranked by the IMF, include Canada, France, Germany, Italy, Japan, the United Kingdom and the United States. The developed countries chosen for this particular study will include Germany, Japan, the United Kingdom, and United States. The reasons for choosing these specific four countries are as follows:

- The United States was chosen for comparability purposes as the studies of Chen, Roll and Ross (1986) as well as Da, Engelberg and Gao (2015) were conducted in the US market.
- Germany and the United Kingdom were chosen due to the size of their economies and prominence in the European Union. Understanding the drivers of two of the largest European economies will ensure the results are far reaching and relevant.
- Japan was chosen as it is the only Asian country in the G7 and its inclusion will include an additional layer of insight to the international nature of this study.
- Applying the same reasoning as the previous bullet points, the remaining countries in the G7 – Italy, France and Canada – were excluded. That is, comparability, size of the economy and geographic diversity.

3.1.2 Country-Specific Market Data

For all BRICS and the selected G7 countries, market index data is required as the independent variable of the regression equation. The closing prices for each market index are gathered on a monthly basis for the various sample periods.

3.1.3 Choice of APT Factors

The choice of APT factors will be closely aligned with the initial empirical work conducted by Chen, Roll and Ross (1986). The following independent variables, collected on a monthly basis, will be the input/ explanatory factors into the APT:

1. Risk free rate – for the purposes of this study, a one year government bond is used to represent the risk free rate. This is true for all countries except South Africa, where instead the discount rate on a 90 day Treasury bill is used.
2. Long-term government bond – for all countries under consideration, a 10 year government bond is used.
3. Inflation – this measure can either be extracted directly or derived using a country's consumer price index (CPI). In this case, a combination of inflation percentages and CPI index data is gathered, dependent on each country.
4. Industrial production – for all countries under consideration, an industrial production index or a producer price index (PPI) is used.
5. Return on high yield bonds – this factor is seen to represent the trade-off between return and risk – higher risk implies higher return. Chen, Roll and Ross (1986) measured this using the return for bonds rated Baa and under. This data is available for the US, but is challenging to retrieve for the remaining countries under examination. Thus, this study employs a variety of high yield bond indices (which track non-investment grade bonds) to capture the risk-return relationship. Table 1 below describes which index will be used for each country.

Table 1: High Yield Bond Indices

Country	Index	Frequency	Abbreviation
United States	Bloomberg USD High Yield Corporate Bond Index	Monthly	BUHY
United Kingdom	Bloomberg GBP High Yield Corporate Bond Index	Monthly	BGBH

Germany	Bloomberg EUR High Yield Corporate Bond Index	Monthly	BEUH
Brazil, Russia, India, South Africa	Bloomberg USD High Yield Emerging Market Corporate Bond Index	Monthly	BEAC
China, Japan	Barclays USD Asia High Yield Bond Index	Monthly	AHYG

6. Oil price – this is simply measured as the price of a barrel of crude oil in each country's respective currency.

The data for each of the factors provided above is collected for each of the countries outlined in Section 3.1.1 above, in line with the different sample periods chosen for each of the countries.

In all cases the data for each country was complete for the entire sample period, barring one: the Brazil 10 year government bond. The data extracted from Bloomberg had a number of missing data points, specifically between January 2010 and May 2010. There was however data on either side of those dates, which made interpolation possible. There are various interpolation methods which could be applied in a scenario such as this one (Bourke, 1999).

- Linear interpolation involves simply joining the points straight line segments; however this method is not very precise, especially for non-linear functions, and can sometimes result in discontinuities at each point and hence is not as smooth an interpolation as one would desire.
- Polynomial interpolation estimates values between known data points using a polynomial function. This method becomes problematic, however, if the underlying data is not a true polynomial.
- Cardinal spline interpolation is a subset of Hermite interpolation and is the simplest method that guarantees true continuity between data points. This is because it requires more than just the two endpoints of the data segment, but also the two data points on either side of them. As it provides a 'smoother' interpolant, it is also more accurate than linear interpolation.

Given the need to have a continuous and smooth data set following the interpolation, the Cardinal Spline method was employed. When there are missing data points in a data set, the Cardinal Spline method uses the previous two non-missing values and the next two non-missing values and tries to fit the missing data to a non-linear or curved pattern. The data is interpolated according to the formula below:

$$\begin{aligned} IV_{CS} = {} & (2\lambda^3 - 3\lambda^2 - 1)P_{i-1} + (1-t)(\lambda^3 - 2\lambda^2 + \lambda)(P_{i+1} - P_{i-2}) \\ & - (2\lambda^3 - 3\lambda^2)P_{i+1} + (1-t)(\lambda^3 - \lambda^2)(P_{i+2} - P_{i-1}) \end{aligned} \qquad \textbf{(12)}$$

Where P_{i-2} and P_{i-1} denote the previous two non-missing values,
P_{i+1} and P_{i+2} denote the next two non-missing values,
λ is the relative position of the missing value divided by the total number of missing values in a row, and
t is the tension parameter and affects the curvature of the spline

Using Cardinal Spline interpolation allowed the data gap to be filled, ensuring that a data set for the entire sample period is used.

As a final point about the choice of APT factors, there is literature to support that country-specific macroeconomic factors might play a greater explanatory role in explaining the returns of that specific country. However, a uniform data set will be applied across all countries. The motivation behind this, although discussed in Section 2.2.2, is due to the following:

- The basis of this study is fundamentally asset pricing; however a specific focus was put on the role of investor sentiment in explaining returns and not which macroeconomic factors have more explanatory power across different countries.
- Holding the macroeconomic variables constant allows for the full effects of investor sentiment to be isolated.
- A uniform set of macroeconomic variables allows for a comparison across the various countries, as any potential results could not be due to differences in explanatory variables.
- Uniformity allows for a comparison between countries as the method applied should provide a much ‘cleaner’ result.

The country-specific data set chosen to satisfy the requirements for each independent variable, its source and frequency is outlined in Table A1 in Appendix A.

3.1.4 Measure of Media Sentiment

As this study will replicate the FEARS index of Da, Engelberg and Gao (2015), the methodology will be closely aligned to their methodology. Recent literature in textual analysis uses the Harvard IV-4 Dictionary as well as the Lasswell Value Dictionary as a starting point (Tetlock, 2007; Tetlock, Saar-Tsechansky, & Macskassy, 2008). These dictionaries classify words into categories such as "positive", "negative", "weak" and so on; the purpose of the FEARS index, however, is to capture household sentiment towards the economy, hence words that are "economic" and have either "positive" or "negative" sentiment are chosen.[8] These search filters results in a list of 163 words; 92 related to positive sentiment and 71 related to negative sentiment. This initial list of words, termed the primitive word list, includes words such as "unemployed", "poverty", "prosper", "affluent", "crisis" and "bankruptcy".

The next step is then to understand how each word in the primitive word list is searched in Google. Each primitive word is inputted into Google Trends which returns the top searches related to that specific word. This will then generate a list of terms related to each word in the primitive list.

The next step is to eliminate the terms that have insufficient data. Finally, the terms that are clearly not related to economics or finance are removed. For example, if one were to input "depression" into Google Trends, the related searches would include "depression symptoms", "depression signs", and "postpartum depression". These topics are not related to economics or finance and hence are removed. This process was completed for all search words.

The steps outlined above generate a list of words that are related to the original primitive list of economic words, free of duplicates, have sufficient observations and include only words related to economics and finance.

Thereafter, the SVI for each word in the final list is downloaded from Google Trends for the different sample periods for each country. This data is collected on a country by country basis

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[8] Specifically, from http://www.wjh.harvard.edu/~inquirer/spreadsheet_guide.htm all economic words (those with tags "Econ@" or "ECON") which also have a positive or negative sentiment tag (those with tags "Ngtv", "Negativ", "Postiv", or "Pstv") are chosen.

for all countries under observation; Google Trends makes this possible via a country filter function, which uses the IP address[9] of a given search term to track where someone is accessing content from. This implies that the data extracted for each country will represent the sentiment of the households of that specific country.

Unlike all the macroeconomic data mentioned above, some of the Google Trends data is provided on a weekly basis. Therefore, data transformation is required to match the high frequency data (Google SVI data) to the lower frequency data (macroeconomic data). The solution employed to achieve this is to take a weekly average in order to obtain a monthly data point. Specifically,

$$SVI_{Monthly} = \frac{SVI_1 + SVI_2 + \cdots + SVI_n}{n} \quad \textbf{(13)}$$

Where n is the number of weeks in any given month

Thereafter, the monthly change in search term j will be calculated as follows:

$$\Delta SVI_{j,t} = \ln(SVI_{j,t}) - \ln(SVI_{j,t-1}) \quad \textbf{(14)}$$

An important aspect of Google Trends data is that it is subject to extreme values, specifically seasonality and heteroscedasticity (Da, Engelberg, & Gao, 2015). To mitigate these concerns, the raw data is adjusted as follows:

- Each series is winsorised[10] at the 5% level (2.5% in each tail).
- To eliminate seasonality from $\Delta SVI_{j,t}$, it is regressed on month dummies and the residual is kept.
- To address heteroscedasticity and comparability, each time series is standardised by scaling each by the time series standard deviation.

[9] An IP address is the numerical label that is attached to a device, for example a computer or tablet which enables location identification.

[10] This is a method of transforming the data by limiting extreme values or outliers. Typically, all outliers are set to a specified percentile of the data.

As such, the final product is an adjusted (winsorised, deseasonalised and standardised) monthly change in search volume, $\Delta ASVI_{j,t}$, for each of the search words.

The final step in creating the FEARS index is to let the data identify which search terms are most important for returns. This can be determined by running expanding backward rolling regressions of $\Delta ASVI_{j,t}$ on market returns to determine the historic relationship between search and contemporaneous market return for each of the search terms. For example, a sentiment value for February 2015 is obtained by regressing any given word on market returns from the start of the sample period until January 2015. Similarly, a sentiment value for March 2015 is obtained by regressing any given word on market returns from the start of the sample period until February 2015.

This step will indicate that if a search term has a strong relationship with the market, whether that relationship is a positive or negative one. In six out of nine countries where a search word had a strong relationship with the market, it was almost always negative. This occurs even though both positive and negative economic words were included from the Harvard and Lasswell dictionaries. This is consistent with the findings of Tetlock (2007) and Da, Engelberg and Gao (2015) who found that negative terms in the English language appear to be the most useful for identifying sentiment. This finding also gives strong support to the positive-negative asymmetry theory which highlights that when it comes to news or shocks, one tends to observe a greater impact of the negative news than the positive news (see Section 2.3.5). The countries where a negative relationship was found include Brazil, India, Germany, SA, the UK, and US.

Conversely, for the remaining three countries – China, Japan, and Russia – where a strong relationship between a search word and the market was found, this relationship was almost always positive in nature. Once again, this occurs despite having included both positive and negative economic words from the Harvard and Lasswell dictionaries. Although these findings are contrary to what would be expected, it is worth noting that the body of research pertaining to sentiment and positive-negative asymmetry in these countries is not as extensive as those mentioned above.

Given the above, the t-statistic from each word and each regression is ranked from most negative to most positive (for six out of nine countries) and most positive to most negative (for three out of nine countries). Thereafter, the top thirty terms are then used to form the FEARS index for each country[11].

Formally, FEARS at month *t* can be defined as follows:

$$\mathrm{FEARS_t} = \sum_{i=1}^{n} R^i(\Delta ASVI_t) \tag{15}$$

Where *n* will represent the number of search words in the sample, and R^i is the ranking of the t-statistics

Given the relatively short sample period, an expanding rolling window is chosen to maximise the statistical power of the selection. The cut-off of thirty is chosen as it is often considered to be the minimum number of observations needed to diversify away idiosyncratic noise (Da, Engelberg, & Gao, 2015).

This historic regression-based approach of selecting terms is advantageous in that it allows the data to "speak for itself". It brings to light words that were not *ex ante* obvious, and is also an objective way of selecting search terms. For example, a word that may be considered to be an economic word of positive sentiment by the Harvard and Lasswell dictionaries may be found to have a negative relationship with market returns.

3.2 Methodology

3.2.1 The APT

The methodology to estimate the factors in an APT model will closely follow that of Chen, Roll and Ross (1986).

The independent variable in each APT model will be the returns on the market indices of the countries under examination. Using the closing prices of each index[12], a return is calculated as follows:

$$Return_t = \ln\left(\frac{Closing\ Price_t}{Closing\ Price_{t-1}}\right) \tag{16}$$

[11] Please see Appendix C for the list of words used for each country's FEARS index
[12] All closing prices have been adjusted for dividends

Table 2 below outlines the explanatory variables that will be included in this study, as well as how they are defined.

Table 2: Definitions of Explanatory Variables

Symbol	Variable	Definition
I	Inflation	Percentage change in a country's consumer price index
GB	Treasury bill rate	Return on a one year government bond
LTB	Long-term Government Bonds	Return on a 10 year government bond
IP	Industrial Production	Percentage change in a country's producer price index
LGB	Low Grade Bonds	Return on a high yield bond index
VWE	Value-Weighted Equities	Return on a value-weighted portfolio of shares specific to a given country
OP	Oil Price	Log relative of Producer Price Index/ Petroleum series

From the variables outlined in Table 2, a further series of variables is defined, shown in Table 3 below.

Table 3: Definitions of Derived Variables

Symbol	Variable	Definition
MP_t	Monthly growth in industrial production	$\left[\frac{IP_t}{IP_{t-1}}\right] - 1$
I_t	Monthly inflation	$\left[\frac{CPI_t}{CPI_{t-1}}\right] - 1$
RI_t	Real interest rate	$GB_{t-1} - I_t$
RP_t	Risk premium	$LGB_t - LTB_t$
TS_t	Term structure	$LTB_t - GB_{t-1}$

Due to the nature of the economic variables used, it is necessary to conduct a correlation analysis as it would reveal relationships between the variables and provide an indication of which variables may give spurious statistical results. The correlation and results will also indicate which variables may be redundant as their effects might be captured in a different variable.

In addition to the variables outlined in Table 2 above, the FEARS index will be included as a further independent variable. These explanatory variables will then be regressed against market indices for the countries outlined in Section 3.1 above. Mathematically, the regression equation will take the following form:

$$R_M = a + \beta_{MP}MP + \beta_I I + \beta_{RI}RI + \beta_{RP}RP + \beta_{TS}TS + \beta_{FEARS}FEARS + \varepsilon \quad \textbf{(17)}$$

It is important to highlight that equation (17) is also a mathematical representation of the fact that the objective of this study is to determine the feasibility of various APT factors, one of which happens to be investor sentiment.

3.2.2 Robustness Checks

A critical component of any empirical analysis, particularly regression testing, is robustness checks. This refers to how certain core regression coefficient estimates behave when the regression specification is altered in some way (Lu & White, 2014). A number of robustness checks will be completed for this study to provide strong support to the results.

3.2.2.1 Controlling for Endogeneity

Given that the FEARS index is based on search volumes, it becomes necessary to determine whether FEARS is a response to traditional market factors or not. Essentially, the nature of the index implies endogeneity could be an issue when running the regression outlined above. Endogeneity refers to one or more of the variables in the regression being correlated with the error term (Wooldridge, 2013). In this particular case, endogeneity can be caused by a loop of causality between the independent and dependent variables in the regression model.

Identifying endogeneity will be carried out using a correlation test between the residual of the model and each individual variable. If the variable is statistically significantly correlated with the residual of the model, then it can be concluded that the specific variable is endogenous. Conversely, if the variable is not statistically significantly correlated with the residual of the model, then it can be concluded that that specific variable is exogenous.

In order to overcome any possible endogeneity in this regression, the instrumental variable (IV) method will be employed. IV involves replacing the dependent variables with predicted values of those same variables that satisfy the following two conditions: 1) Exogeneity: the IV must be uncorrelated with the error term of the model and 2) Relevance: the IV is correlated with the independent variable. Only once both these conditions are satisfied is a variable considered to be an IV. This process will ensure that a consistent regression coefficient is obtained. In the instance of one variable being found endogenous, only one instrument is necessary and hence this instrument can be included in a standard OLS regression. This is performed in two steps; step one involves obtaining the IV values and step two involves running an OLS regression, but replacing the endogenous variable with the IV estimator. In the event of multiple endogenous variables and hence multiple instruments, the Two Stage Least Suqares (2SLS) regression method is applied. The 2SLS method allows for the inclusion of instrumental variables. The output of this regression, specifically the coefficients and associated p-values, is the same as that derived from an OLS regression (Wooldridge, 2013).

3.2.2.2 Regression-Specific Robustness Checks

In order to determine the robustness of the best suited APT model, the error term of the model needs to be analysed.

First, the error term is tested for stationarity using the Augmented Dickey Fuller test. If the error term is found to be stationary, then this could imply that the model is a suitable fit.

A further test involves testing for Autoregressive Conditional Heteroskedasticity (ARCH) effects in the APT model. Essentially, this tests if the monthly return series is non-constant and if the squares of the monthly return series are correlated. The Lagrange Multiplier (LM) test statistic and its associated p-value are used to determine the presence of ARCH effects. However, an additional test, the Breusch-Godfrey test, is employed to ensure the result is robust. If the LM finds no ARCH effects, this does not necessarily imply that the conditional variance of the monthly return series is constant; this can occur if disturbance terms are serially correlated. Hence, the Breusch-Godfrey test is employed as a serial correlation LM test.

The stability of the regression model also needs to be tested; this is done through a number of diagnostic tests.

- Leverage plots – this will show how well the explanatory variables fit the model.
- Influence statistics – the influence statistics for the RStudent, Hat Matrix, DFFITS and COVRATIO will identify any possible outliers in the model.

- Scaled difference in coefficients (DFBETAS) – this will also give an indications of the possible outliers in the model.

3.2.2.3 Volatility and FEARS Correlation Tests

There is evidence from Black (1986) which suggests that both investor sentiment and the noise trading effect can affect both the level and volatility of asset prices. If uninformed noise traders made decisions based on sentiment, then any extreme sentiment changes will temporarily lead to more noise trading, greater mispricing, and excessive volatility. If this holds true, then any changes in FEARS will be accompanied by a change in volatility – which will lend support to the noise trading theory outlined by DeLong, Shleifer, Summers and Waldman (1990). Moreover, this will also provide an indication as to whether any relationships found in the regression analysis are true statistical relationships or are merely caused by correlation with a volatility index.

As such, a correlation analysis will be run on the FEARS index against its respective country-specific volatility index, where available.

Of the nine countries under examination, six have their own volatility indices as outlined in Table 4 below. As for the countries where no volatility index was available, they were excluded from the correlation analysis.

Table 4: Volatility Indices for Countries

Country	Volatility Index	Source
Brazil	Not available	
Russia	Removed due to insufficient data	
India	India VIX	Bloomberg
China	Not available	
South Africa	South African Volatility Index	JSE
Germany	Volatility DAX	Bloomberg
Japan	Nikkei VIX	Bloomberg
United Kingdom	FTSE 100 VIX	Bloomberg
United States	S&P 500 VIX	Bloomberg

This section outlined the methodology that will be undertaken to address the validity of the hypotheses presented in Sections 1.3.1 and 1.3.2 above. It describes the macroeconomic explanatory variables employed as well as the form the regression equation will take once completed. Furthermore, numerous robustness checks are outlined to ascertain the strength of the regression output.

4 Results

This chapter, as well as Appendices B and C, present the results of the various tests described in Section 3.2 as well as the discussion of the results on an individual country basis. The regression results are shown below; Table 5 for BRICS and Table 6 for the selected G7 nations.

The discussion of each country's results is structured by: 1) Understanding the role a country's economic and financial history has in explaining their regression results and 2) Understanding why investor sentiment is statistically significant in some countries and not in others. The discussion on the latter point includes, but is not limited to, the strength of a country's regulatory bodies, the level of trust investors have in the country's economy and capital market, the level of sophistication of the country's investors and the level of Individualism prevalent in the country's society[13]. Thereafter, the results of all the countries are considered together to identify a number of key outcomes and implications for the study overall.

[13] Individualism is measured using Hofstede's (2001) cultural dimension theory which serves as a framework for cross-cultural communication. It describes the effects of a society's culture on the values of its members and how these relate to behaviour. The dimensions employed in the index include: power distance, individualism, masculinity, uncertainty avoidance, long-term orientation and indulgence. The Individualism dimension, specifically, describes the degree of interdependence a society maintains among its members. The scale is from 1 to 120, with a higher score indicating a more individualistic society. Recently, this index has been used to understand the link between individualism and momentum in a given market. It has also been used to understand the link between individualism and the effects of investor sentiment – the higher the score on the Individualism dimension, the lower the effects of investor sentiment should be.

Table 5: Regression Results: BRICS

		Intercept	Inflation	Industrial Production	Real Interest Rate	Risk Premium	Term Structure	Oil Price	FEARS	R^2	Adjusted R^2
Brazil [BOVESPA]	1	-0.013313	0.344756	-0.416924	1.381797	1.482409	1.392697	-0.021228		0.478923	0.425019
		[0.5266]	[0.8346]	[0.2261]	[0.0000]*	[0.0000]*	[0.0000]*	[0.7197]			
	2	-0.015895	0.418664	-0.401074	1.312081	1.41665	1.328835	-0.028402	-0.000689	0.486513	0.423453
		[0.4547]	[0.8004]	[0.2454]	[0.0000]*	[0.0000]*	[0.0000]*	[0.6348]	[0.3626]		
Russia [MICEX]	1	0.006105	1.967105	-0.138815	0.867847	0.915265	0.705785	0.019132		0.41256	0.35179
		[0.9685]	[0.048]*	[0.677]	[0.0297]*	[0.0026]*	[0.0607]**	[0.9168]			
	2	-0.0324	1.635386	-0.22407	0.468437	0.602142	0.330203	-0.031428	0.00163	0.455309	0.388417
		[0.8306]	[0.0935]**	[0.4928]	[0.2724]	[0.0645]**	[0.4125]	[0.8611]	[0.0388]*		
India [NIFTY]	1	-0.067827	-1.666947	0.131386	0.534003	1.092711	0.667758	-0.050215		0.340932	0.272752
		[0.3837]	[0.2949]	[0.1342]	[0.0617]**	[0.0000]*	[0.0197]	[0.3441]			
	2	-0.073028	-1.578942	0.132683	0.475522	1.043976	0.618219	-0.053738	-0.000457	0.350263	0.27047
		[0.3507]	[0.3226]	[0.1312]	[0.1043]	[0.0000]*	[0.0338]*	[0.3137]	[0.3694]		
China [SSE]	1	0.244624	0.084473	1.374127	0.578255	0.404908	0.458733	0.294306		0.186796	0.04739
		[0.0063]*	[0.9729]	[0.5841]	[0.4185]	[0.4842]	[0.5233]	[0.0096]*			
	2	0.245379	0.053802	1.370932	0.588014	0.409972	0.467035	0.295176	-0.000044	0.186901	0.019498
		[0.0074]*	[0.9833]	[0.5905]	[0.4272]	[0.4889]	[0.5281]	[0.0111]	[0.9477]		

South Africa [ALSI]	1	-0.012058	0.125129	-0.637855	0.811492	0.802582	0.81412	-0.026076		0.32706	0.257446
		[0.7734]	[0.9087]	[0.3393]	[0.0018]*	[0.0000]*	[0.0001]*	[0.5773]			
	2	-0.013107	0.164039	-0.421562	0.649494	0.677961	0.657736	-0.0253	-0.00159	0.476798	0.412545
		[0.7250]	[0.8658]	[0.4788]	[0.0053]*	[0.0000]*	[0.0007]*	[0.5433]	[0.0002]*		

Note: p-values for coefficients provided in the square brackets below the coefficient

*Statistically significant at the 5% level of significance; **Statistically significant at the 10% level of significance

Table 6: Regression Results: Selected G7 Countries

		Intercept	Inflation	Industrial Production	Real Interest Rate	Risk Premium	Term Structure	Oil Price	FEARS	R^2	Adjusted R^2
Germany [DAX]	1	-0.025138	1.995865	1.562822	1.664428	1.676344	-0.025138	0.124068		0.541707	0.494298
		[0.0592]**	[0.1586]	[0.2379]	[0.0000]*	[0.0000]*	[0.0000]*	[0.0706]			
	2	-0.021672	1.984123	1.172157	1.541898	1.559616	-0.025138	0.108609	-0.000873	0.556313	0.501825
		[0.1064]	[0.158]	[0.3824]	[0.0000]*	[0.0000]*	[0.0000]*	[0.1147]	[0.1761]		
Japan [NIKKEI]	1	-0.000415	0.148215	0.416378	0.279035	0.19571	0.304085	-0.010721		0.133348	-0.01522
		[0.9984]	[0.9339]	[0.4591]	[0.5303]	[0.6645]	[0.4943]	[0.9176]			
	2	0.128551	0.148215	0.178799	0.104828	0.022166	0.111331	0.054845	0.002599	0.293726	0.148317
		[0.5039]	[0.9339]	[0.7314]	[0.7988]	[0.9577]	[0.7872]	[0.576]	[0.0088]*		
UK [FTSE100]	1	0.019087	-5.859118	0.929621	-4.913118	-0.151151	-0.109817	0.02177		0.09536	0.000135
		[0.4636]	[0.281]	[0.103]	[0.3737]	[0.4026]	[0.5453]	[0.7617]			
	2	0.021142	-5.358581	0.978014	-4.556404	-0.127387	-0.110349	0.007593	-0.001979	0.387728	0.311194
		[0.3291]	[0.2355]	[0.0403]*	[0.3208]	[0.3957]	[0.4644]	[0.8987]	[0.0000]*		
US [S&P500]	1	0.015456	-0.593695	-0.355041	0.018349	-0.208591	-0.003804	-0.039876		0.306652	0.234926
		[0.006]*	[0.6446]	[0.7274]	[0.9459]	[0.4484]	[0.9888]	[0.34]			
	2	0.015536	-0.355804	-0.232572	-0.0907	-0.290737	-0.103379	-0.044406	-0.001111	0.408569	0.335937
		[0.0032]*	[0.767]	[0.8065]	[0.7217]	[0.2607]	[0.6845]	[0.2553]	[0.0027]*		

Note: p-values for coefficients provided in the square brackets below the coefficient

*Statistically significant at the 5% level of significance; **Statistically significant at the 10% level of significance

4.1 BRICS Nations

4.1.1 Brazil

The regression results in Table 5 above show the two regression models; (1) and (2). Model (1) is the macroeconomic APT model without the FEARS variable. This model explains 42.5% of the variation in Bovespa returns; the real interest rate, risk premium, and term structure variables are all statistically significant at the 5% level of significance. Moreover, the variables share a positive relationship with Bovespa returns, which implies that any increases in these variables will result in an increase in Bovespa returns. Model (2) is the macroeconomic APT model with the FEARS variable. This model explains 42.3% of the variation in Bovespa returns – this is lower than (1) implying that the addition of the FEARS variable does not improve the explanatory power of the model. Moreover, the FEARS variable itself is statistically insignificant. The same variables from (1) are found to be statistically significant at the 5% level of significance in (2). This relationship remains positive; however, the strength of the relationship is somewhat reduced in (2).

The macroeconomic nature of the variables warranted a correlation analysis, to ascertain the presence of any correlation between variables (Table C1 in Appendix C). This analysis showed that the three variables mentioned above are statistically significantly correlated with each other at the 5% level of significance; this is not surprising as all three variables are related to the interest rate as they are in some way related to the government bond return. A step-wise regression procedure indicated that the real interest rate variable is redundant as its effects are likely captured in the other two interest rate-related variables. This implies that the explanation of Bovespa returns is properly captured by the risk premium and term structure variables, with FEARS playing no statistically significant role in explaining Bovespa returns. As such, it would appear that (1) is a superior model for explaining Bovespa returns.

When considering why the real interest rate, risk premium, and term structure variables were found to play a significant role in explaining Bovespa returns, it is useful to understand the macroeconomic drivers in the market. Research into what exactly influences interest rates in Brazil has found that macroeconomic conditions play the primary role in determining interest rates. Macroeconomic conditions are measured using variables such as inflation, risk premium, economic activity and required reserves (Afanasieff, Lhacer, & Nakane, 2002). In addition, the interest rate was also found to have significant explanatory power in explaining business cycles in Brazil, which in turn affects the performance of the stock market (Neumeyer & Perri, 2005).

If this result is used to explain the outcome of the Brazil APT, the other explanatory factors employed in this study actually explain interest rate movements in Brazil. This explains why only the interest rate variables were found to be statistically significant – the remaining variables determine the country's interest rates. The explanatory power of the risk premium can be explained by acknowledging that Brazil is perceived as a high risk country; in fact it was ranked as the eighth most risky country by Bank of America Merrill Lynch (2015)[14], implying that there is a high risk of default. As such, investors would require additional compensation for taking on this risk and hence it would be expected that the risk premium paid to investors has explanatory power for market returns.

The fact that FEARS did not contribute any explanatory power to the regression model does not necessarily imply that investor sentiment is not an explanatory factor in the Brazilian market. From the literature, it is quite clear that there are a number of different ways to measure investor sentiment, with each one capturing something different. It is possible that in the Brazilian market investor sentiment is better captured through market proxies (Yoshinaga & De Castro Junior, 2012) or even textual analysis on news articles (Daszyńska-Żygadło, Szpulak, & Szyszka, 2014), tweets, and Facebook posts. Culturally, Brazil is viewed to be a collectivist nation – they score 38 on the Individualism dimension on Hofstede's (2001) culture index. In a collectivist culture, it is expected that the effects of investor sentiment are larger (Schmeling, 2008). Therefore, using an alternative measurement of investor sentiment could provide support for this hypothesis.

The results of the regression as well as the economic history and theory outlined above indicate that interest rates are pivotal to Brazil's economy and stock market. A thorough understanding of this link is critical as it has implications for those participating in the capital market, such as traders, as well as those making policy decisions. The results can therefore be used in assisting traders in making larger profits, as well as policy decision makers to ensure they are acting in the best interests of the economy. The regression results indicated that FEARS did not display statistically significant explanatory power in the market; however, this does not necessarily mean that investor sentiment does not have explanatory power in the Brazilian stock market. There is evidence which indicates that investor sentiment, measured in a different way, does have an impact on the Brazilian market.

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[14] This is determined by a credit default swap spread which measures the risk of default on sovereign debt – the higher the spread, the greater the risk of default.

4.1.2 Russia

The regression results in Table 5 above show the two regression models; (1) and (2). Model (1) is the macroeconomic APT without the FEARS variable. This model explains 35.1% of the variation in Micex returns; the inflation rate, real interest rate, risk premium, and term structure are all statistically significant at the 5% level of significance. Moreover, all these variables share a positive relationship with Micex returns, which implies that any increases in any of these variables will result in an increase in Micex returns. Model (2) is the macroeconomic APT model with the FEARS variable. This model explains 38.8% of the variation in Micex returns. This is higher than (1) which implies that the addition of the FEARS variable improves the overall explanatory power of the model. Unfortunately, the inclusion of the FEARS variable causes the real interest rate and risk premium variables to become statistically insignificant. It also changes the level of significance in both the inflation rate and risk premium variables – these variables now become statistically significant at the 10% level of significance instead of the 5% level of significance as in (1). Moreover, the magnitude of the relationship between the inflation rate and risk premium and Micex returns has also been adversely affected. The investor sentiment variable, FEARS, is statistically significant at the 5% level of significance and it shares a positive relationship with Micex returns. This implies that any increases in investor sentiment will be matched by increases in Micex returns; seeing that the FEARS index for Russia was constructed with predominantly positive economic words, this is expected as an increase in positive investor sentiment will have a positive impact on Micex returns. From (2) is appears that FEARS is a statistically and economically significant explanatory variable in the Russian macro-economy.

The macroeconomic nature of the variables warranted a correlation analysis, to ascertain the presence of any correlation between variables (Table C2 in Appendix C). Correlations between variables were found to be relatively weak as many of the coefficients are closer to 0 than to 1. Inflation appears to be correlated with industrial production; this is quite expected as both variables are measures of the rising cost of goods. The term structure variable is negatively and statistically significantly correlated with both the real interest rate and risk premium variables. This is similar to what was uncovered in the Brazil correlation analysis; these variables are likely to be correlated due to their relationship with the government bond return. A step-wise regression procedure revealed that the industrial production and real interest variables are likely to be redundant. As such, the variation in Micex is best explained by the inflation rate, the risk premium, and FEARS. As such, it would appear that (2) is a superior model for explaining Micex returns.

The Russian market and its development is a function of the history and current state of the country; a better understanding of this is likely to yield insight into the results of the regression. The Russian stock market, as it is known today, began in the early 1990s amidst political and economic transformation. The first few years saw a rapid increase in stock turnover; however, this occurred with no market regulation or formalised trading platform. The lack of a supervisory body to oversee the capital market resulted in numerous scandals, including pyramid schemes. Although a regulatory body was eventually established, reforms were carried out to a relatively limited extent; this was caused by a lack of enforcement and limited penalties. The underlying cause, however, is the weakness of the Russian judicial system as a whole. The consequences of a lack of market supervision include insufficient trading security, corruption, and a lack of transparency in reporting standards (Marszk, 2013).

Inflation is an important factor in the development of a stock market (Vasiliev, 2010) and a low inflation rate is indicative of macroeconomic stability (Yartey, 2008). Russia's inflation rate, however, is extremely high which indicates a level of macroeconomic instability in the country. Their historically high inflation rates have been crippling to the economy and have not yet stabilised to the point where it encourages economic development. The positive relationship between inflation and Micex returns found is also inconsistent with what theory dictates in the short-term – high inflation reduces an individuals' purchasing power which increases input prices, drives the demand for goods down resulting in lower revenues and ultimately a slowdown in the economy (Ammer, 1994). In the longer term, however, the additional costs are passed to consumers and hence stock prices will rise in line with increased inflation. The inconsistency could be pinned down to the underdeveloped nature of the Russian stock market.

The explanatory power of the risk premium variable is likely driven by the fact that the most important factor affecting the cross-section of Russian returns is in fact the country's risk (Goriaev, 2004). The description of the Russian stock market outlined above provides many reasons as to why investment in this market could be deemed risky for all investors, and hence why investors would demand a premium as an incentive to invest in the market. This can be confirmed by Bank of America Merrill Lynch (2015) who reported that Russia is seventh on a list of countries most likely to default on their sovereign debt.

The immaturity of regulation in the Russian stock market, coupled with the fact that the market is relatively underdeveloped has consequences for overall market performance. An immature regulation framework creates a level of distrust in the institution of a stock market; this drives investors to seek alternative methods or mediums of investing, such as through commodities. Moreover, the impact of investor sentiment on the market tends to be stronger in those markets which have less market integrity (Schmeling, 2008). An underdeveloped market also suffers from a lack of information, particularly good quality and complete information. When investors are forced to make decisions with incomplete or overly complex information, they tend to rely on simplified heuristics or rules of thumb (De Martino, Kumaram, Seymour, & Dolan, 2006). This affects their ability to make an informed decision as this process becomes clouded by cognitive and behavioural biases. Further insight about the role culture plays in explaining the effects of investor sentiment can be gained from Hofstede (2001). Russia scores 39 on the Individualism dimension implying that Russian culture is more collective and inclusive. In instances of low individualism, investor sentiment is expected to have a larger impact on market returns (Schmeling, 2008). Given the nature of the Russian stock market as well as its collectivism culture, it is quite expected that investor sentiment plays a role in explaining market returns.

The results of the regression as well as the overview provided of the Russian macro-economy and stock market show that the inflation rate, the risk premium and investor sentiment play a pivotal role in explaining movement in Micex returns. Furthermore, a link can be drawn between these results and how they can be used by traders and those making policy decisions. Investor sentiment, as measured by FEARS, was found to be statistically significant in explaining Micex returns. This can be explained by several characteristics of the Russian market which make it susceptible to the effects of investor sentiment.

4.1.3 India

The regression results in Table 5 above show the two regression models; (1) and (2). Model (1) is the macroeconomic APT without the FEARS variable. This model explains 27.3% of the variation in Nifty returns; the risk premium was found to be statistically significant at the 5% level of significance whereas the real interest rate variable was found to be statistically significant at the 10% level of significance. Both variables were found to share a positive relationship with Nifty returns. This implies that any increases in the real interest rate and/or risk premium variables would result in an increase in Nifty returns. The lack of explanatory power of the industrial production variable is unexpected as there is evidence to suggest that industrial production has strong explanatory power for the Indian stock market (Patel, 2012; Naka, Mukherjee, & Tufte, 1998). Model (2) is the macroeconomic APT with the FEARS variable included. This model explains 27% of the variation in Nifty returns; this is lower than (1) indicating that the inclusion of the FEARS variable did not improve the explanatory power of the model. Nevertheless, both the risk premium and term structure variables were found to be statistically significant at the 5% level of significance. The inclusion of the FEARS variable has resulted in the real interest rate variable losing its statistical significance; however, the term structure variable appeared to have gained statistical significance. Both these variables were also found to share a positive relationship with Nifty returns, with the strength of the risk premium variable being reduced somewhat.

A correlation analysis was also completed to ascertain any potential correlations between the macroeconomic variables (Table C3 in Appendix C). The term structure and real interest rate variables were found to be statistically significantly correlated at the 5% level of significance; Nifty returns and the risk premium variables were also found to be positively and statistically significantly correlated at the 5% level of significance. The relationship between Nifty returns and the risk premium is understandable as investors require additional compensation to take on any additional risk which would increase the overall rate of return on a specific asset, hence affecting the market positively. The relationship between the term structure and real interest rate variables is also understandable as both these variables are related to the government bond return; it is likely that one of these variables is redundant in the regression model. When the step-wise regression was completed, it was found that the real interest rate variable is likely redundant. As such, it would appear that (1) is a superior model for explaining the variation in Nifty returns.

As an additional check, the correlation analysis between FEARS and the Nifty VIX (Volatility Index) revealed a statistically insignificant relationship (Output (1), Table C10 in Appendix C) between the two variables. Therefore, the regression and correlation results are congruent in that FEARS does not play an explanatory role in the market.

India has emerged as a strong economy over the past years, characterised by high levels of investment and rapid growth across various sectors. Following India’s independence in 1947, the country’s economic growth can be described in phases with each phase characterised by growth and investment in different sectors. Phase 1 (1950 – 1980) was characterised by substantial public investment in basic industries, infrastructure and the agricultural sector. Phase 2 (1981 – 1990) saw India implement industrial and trade reforms which facilitated capacity expansion, modernisation and productivity improvement in the industrial sector. The 3rd phase (1991 – 2010) saw an economic liberalisation in the country, an expansion in the service industry and a rise in private consumption (Bhat, 2013). The 4th and final phase is still under way and is characterised by substantial investment in physical, agricultural and social infrastructure. In the midst of these periods of economic growth and investment, India's monetary policy also went through an evolution.

Historically, India has struggled with high inflation rates and hence interest rates are an important lever used to curb inflation. This coupled with the role interest rate de-regulation has played in developing key segments of India's economy highlights the importance interest rates play in India's macro-economy. The regression results highlighted a positive relationship between real interest rates and Nifty returns which can be explained as follows – when interest rates are increased this encourages consumers to save and invest instead of consume and hence there is an inflow of fund into capital markets which has a positive impact on market prices and their associated returns.

The positive direction of the risk premium relationship can be explained by understanding that additional compensation offered to investors to invest in risky assets results in investors actually investing in such assets, which positively affects market returns. The magnitude of this relationship can be compared to the other countries examined so far; the relationship is stronger than that observed in Russia but slightly weaker than that observed in Brazil. According to the Bank of America Merrill Lynch (2015), India is less risky than both Brazil and Russia and so the regression results are consistent for Brazil and inconsistent for Russia. Further insight into India's risk scores indicates that sovereign and currency risk are not necessarily as great of an issue as banking sector risk. The source of banking sector risk in India stems from a past lending spree which has burdened India's banks with distressed assets. That being said, improved monetary policy has been passed recently which will assist with mitigating a degree of the banking sector risk (The Economist Intelligence Unit, 2016). India's economy is characterised by rapid growth and substantial investment and hence being seen as a growth economy could also be a potential source of risk. The level of credit default risk (Bank of America Merril Lynch, 2015) and banking sector risk (The Economist Intelligence Unit, 2016) explain the positive relationship between the risk premium and Nifty returns.

The fact that FEARS did not contribute any explanatory power to the model does not necessarily imply that investor sentiment does not have an impact on returns in India. As seen in the literature section there are various ways to measure investor sentiment, with each measure capturing different information in a different way. Essentially, it is possible that the FEARS index does not capture investor sentiment adequately and in fact some other measure captures the investor sentiment in India more correctly. It is possible that this could also be driven by country-specific factors as well as the culture of the country. Investor sentiment can be influenced by a variety of factors which are likely to affect its measurement. Evidence on the influencing factors of Indian sentiment have shown that economic, market and regulatory factors have the ability to influence investor sentiment as well as its relationship with market performance (Sehgal, Sood, & Rajput, 2009). The FEARS index is based purely on macroeconomic search word information, with market and regulatory search words likely to have been overlooked. Given the strong level of distrust in the India stock market, especially its regulatory body, this is likely to have a large impact on investor sentiment and by extension its effect on market performance (Kavitha, 2015). Put simply, perhaps FEARS is not a suitable investor sentiment measure in India; with it being better captured using surveys (Chandra & Kumar, 2012; Bennett, Selvam, Vivek, & Shalin, 2012) and market variables (Sehgal, Sood, & Rajput, 2012; Dash & Mahakud, 2013). A cultural lens can also be applied to gain an understanding of the effect of investor sentiment; India has traits of both an individualistic and collectivistic nation as their score on Individualism in Hofstede's (2001) culture index is an intermediate 48. As such, the effects of sentiment are likely to be moderate in a market like this.

Insight into the Indian economy and drivers thereof are consistent with results of macroeconomic regression. Interest rates are an important lever used to manipulate other macroeconomic variables and hence have explanatory power for stock market returns. Moreover, any increases in the risk premium also have a positive impact on market returns as investors have more of an incentive to invest in risky assets. Investor sentiment, as measured by FEARS, was not found to have any statistically significant explanatory power in the regression. However, there is evidence which indicates that investor sentiment captured using surveys or market variables do have explanatory power for market returns. The prevalence of the effects of investor sentiment in a market can be influenced by economic, market and regulatory factors; given this, there are characteristics of the Indian market which imply that investor sentiment could indeed play an explanatory role; however, it could be that investor sentiment is better captured using a different methodology.

4.1.4 China

The regression results in Table 5 above show the two regression models; (1) and (2). Model (1) is the macroeconomic APT without the FEARS variable. This model explains 4.7% of the variation in SSE returns; the oil price and intercept were the only variables found to be statistically significant at the 5% level of significance. Both variables were found to share a positive relationship with SSE returns implying that any increases in these variables would result in an increase in SSE returns. China is the only instance in this study where a relationship was found between the oil price and SSE returns. Model (2) is the macroeconomic APT with the FEARS variable included. This model explains only 1.9% of the variation in SSE returns; this is lower than (1) indicating that the addition of the investor sentiment variable does not have a positive effect on the explanatory power of the model. Moreover, the addition of the FEARS variable has caused the oil price variable to become statistically insignificant while only the intercept remains statistically significant at the 5% level of significance. This regression indicates that investor sentiment, as measured by FEARS, does not play an explanatory role in the Chinese market.

A correlation analysis was also completed to determine any possible sources of correlation amongst the variables (Table C4 in Appendix C). The term structure and real interest rate variables were found to be negatively and statistically significantly correlated at the 5% level of significance. SSE returns were found to share a positive and statistically significant correlation with the oil price, which is consistent with the regression results. Inflation and industrial production were also found to be positively and statistically significantly correlated at the 10% level of significance – given that both variables are a measure of the increase in price of goods, this is expected. Through the step-wise regression procedure it was found that even removing correlated variables did not yield a stronger regression model. As such, (1) appears to be the superior model in explaining the variation in SSE returns.

China is the only instance in this study where a relationship was found between the oil price and market returns. There is some evidence to indicate that oil price shocks do have an impact on market returns in China (Broadstock & Fillis, 2014; Yun & Yoon, 2015). The economic significance of this relationship, however, is interesting as it stems from the building blocks of the Chinese economy. The oil sector plays an important role in China's economy and has also been the focus of major structural reforms and high-level attention from the government. Despite the policy reforms towards more market-oriented oil sector, government ownership, limited foreign investment, and inefficient expansion strategies still characterise the industry. Since 1979, China's demand for oil has surpassed its oil production which has resulted in China becoming one of the top importers of oil in the world. The magnitude of China's demand for oil has dire implications, as their influence on and vulnerability to international oil market is significant. Moreover, this discrepancy between demand and domestic supply is only getting larger, leaving China with tough choices to conquer their energy crisis (Soligo & Jaffe, 2004). As such, the statistical relationship found in the regression also has economic significance.

In terms of explaining the lack of explanatory power of FEARS it is worthwhile to consider the types of investors in China, as well as the nature of the stock market. Retail investors only participate in this market due to the lack of alternative investment opportunities. Moreover, the lack of sophistication of these investors causes them to rely quite heavily on rumours for information, with the market being largely momentum driven (Drew, Naughton, & Veeraraghavan, 2003). Given the relatively short period of trading, as well as the market characteristics it was expected that investor sentiment have a strong impact on returns (Chi, Zhuang, & Song, 2012). The results, however, show that investor sentiment as measured by FEARS does not have any driving force behind the stock market. There could be numerous reasons for this outcome; however, the primary reason is likely due to the fact that Google is banned in mainland China (excluding Hong Kong and Macau) as the Chinese government believes that some of the content contravenes Chinese law. This ban was put into effect in March 2009 and seeing that the sample period for China started after this, Google SVI data would not be useful in explaining investor sentiment in the country. This band also extends to various social media platforms and hence investor sentiment in China is likely to be captured more completely using surveys or market proxies (Chi, Zhuang, & Song, 2012). Based on Hofstede's (2001) culture hypothesis, China is a highly collectivist nation as their Individualism score is 20. As such, it would be expected that the effects of investor sentiment in the market with such low individualism would be substantial. As such, it demonstrates that investor sentiment is likely to play a role in the Chinese stock market provided that investor sentiment is captured by the correct measure.

The results of the regression as well an overview of the Chinese economy, its drivers and its investors indicate that these results are not only statistically significant, but economically significant as well. The regression showed that investor sentiment, as measured by FEARS, did not have any explanatory power for SSE returns. There is evidence, however, that investor sentiment measured in an alternative way has explanatory power in the Chinese market. The primary reason for the lack of explanatory power of FEARS is likely because Google is banned in mainland China (excluding Hong Kong and Macau). Despite the fact that China is an anomaly in this study, the regression results have provided insight into the Chinese stock market and economy.

Attention should also be paid to the fact that the sample size of the China analysis was limited compared to most of the other countries under examination.

4.1.5 South Africa

The regression results in Table 5 above show the two regression models; (1) and (2). Model (1) is the macroeconomic APT without the FEARS variable. This model explains 25.7% of the variation in ALSI returns; the real interest rate, risk premium, and term structure variables were found to be statistically significant at the 5% level of significance. Moreover, all three variables displayed a positive relationship with ALSI returns which implies that any increase in any of those variables would result in an increase in ALSI returns. This link between interest rate variables and the stock market has been found in numerous countries, and South Africa is no different. The link is explained by considering both the institutional and individual perspectives. Company valuations, using the discounted cash flow methodology, will be affected by changes in interest rates which will inevitably affect a firm’s stock price. When numerous companies are affected by these changes, the indices in the market will also be affected. For individuals, higher interest rates serve as an incentive for consumers to save rather than spend due to favourable interest rates on deposit accounts or investments. As such, there will be an inflow of funds into the stock market, where previously this money was flowing into the economy in the form of consumption. Model (2) is the macroeconomic APT with the inclusion of the FEARS variable. This model explains 41.3% of the variation in ALSI returns; this is higher than (1) which implies that the inclusion of the FEARS variable has improved the explanatory power of the overall regression model. The real interest rate, risk premium and term structure variables retain their statistical significance at the 5% level of significance; a positive relationship between these variables and ALSI return was found, however, the magnitude of the relationship has been adversely affected in (2). Investor sentiment, as measured by FEARS, was found to be statistically significant at the 5% level of significance; a negative relationship between FEARS and ALSI returns was found. This implies that any increases in investor sentiment will have a negative impact on ALSI return; this can be explained by the construction of the FEARS index itself. During the index construction process, it was found that negative words have the largest impact on ALSI returns and hence these were the words that were included. Therefore, the FEARS index for South Africa could be thought of as 'negative'; this would explain why an increase in 'negative' investor sentiment would result in a decrease in ALSI returns.

A correlation analysis was completed (Table C5 in Appendix C) and a step-wise regression procedure carried out to determine the possibility of redundant variables. Inflation and industrial production were found to share a positive and statistically significant relationship at 5% level of significance – this correlation is not uncommon as both variables capture the rising cost of goods. The real interest rate, risk premium and term structure variables were found to be positively and statistically significantly correlated at the 5% level of significance – this too is expected as the variables are all related to the government bond return in some way. Despite the results of the correlation analysis, the step-wise regression procedure indicated that there are no redundant variables. As such, it would appear that the real interest rate, risk premium, term structure and investor sentiment variables accurately capture the variation in ALSI returns; hence model (2) is the superior model in explaining ALSI returns.

As an additional check, the correlation analysis between FEARS and the SAVI (Volatility Index) revealed a statistically significant relationship (Output (2), Table C10 in Appendix C) between the two variables. Thus, although FEARS was found to be statistically significant, the correlation analysis finds that this relationship could be driven by noise in the market rather than a true statistical relationship.

SA's history can be used to provide insight into the regression results. The discovery of gold and the formation of mining companies were the driving force behind the establishment of the JSE, which was primarily used to help mining companies with access to capital. The mining industry dominated the JSE and was responsible for the rapid growth in the number of listed companies, market capitalisation and liquidity (Vacu, 2007). Today, the JSE is still dominated by resource stocks which come with their own peculiarities (Auret & Sinclaire, 2006). Although mining formed the foundation of the JSE, according to Statistics South Africa it contributes a very small percentage to the country's GDP; the financial services sector, on the other hand, is the main contributor. The financial services sector operates in a challenging environment but has been measured to be resilient and strong despite this. Regulation and the country's regulatory bodies play a critical role in this as many of the industries in the financial services sector are highly regulated and the South African Reserve Bank as well as industry regulatory bodies play a proactive supervisory role (International Monetary Fund, 2014).

Interest rates appear to have strong explanatory power in the SA market; this is due to the fact that interest rates are the main policy instrument employed by the country's reserve bank in achieving its mandate. Historically, interest rates were used as a means to curb inflation in the country; however, once inflation targeting was employed, movements in the interest rate have become more predictable as inflation targets are quite clear (Hanival & Maia, 2013). An increase in interest rates has an impact on both institutional and individual investors, as highlighted above. Interest rate changes will affect firms through the valuations channels, whereas individuals will be affected through the saving and consumption channels.

The explanatory power of the risk premium is likely driven by the significant risks attached to investing in the SA market and hence investors require additional compensation to do so. Evidence from the Bank of America Merill Lynch (2015) indicates that SA is the eleventh riskiest country based on credit default risk, with a credit default swap spread of between 200 and 500bps (there are only two countries with a CDS spread of greater than 500bps). According to The Institute of Risk Management South Africa (2015), the top 10 risks by likelihood (in descending order) include: corruption, unemployment, infrastructure, political and social instability, organised crime, cyber-attacks, financial mechanism, income disparity, urbanisation and data fraud. Those risks with the largest consequences, however, are corruption, failure in governance and unemployment. Any investor would be susceptible to those risks as well as the associated consequences; as such, investors require additional compensation for choosing to invest in SA. If this compensation is received, investors will choose to invest and this will drive positive movement in the stock market.

Investor sentiment does have statistically significant explanatory power in this market, with the relationship with market returns being negative. This is expected as the SA FEARS index was constructed using mainly 'negative' economic words and hence the index captures negative sentiment. Thus any increases in negative sentiment towards the country will result in a negative impact on market returns. The strength of the financial services sector as well as its highly regulated nature implies that: 1) There should be good quality and complete information available for investors to make informed decisions and 2) There should be an inherent level of investor trust in the regulations and repercussions for wrongdoing. As such, investor sentiment should not necessarily be a driver of financial performance. That being said, SA investors also appear to be strongly influenced by the country's underlying political framework (Mlambo & Oshikoya, 2001), which has been somewhat compromised over the years. Therefore, the level of uncertainty or investor trust extends beyond one sector and is actually applicable to the entire economy, resulting in sentiment-driven financial performance. From a cultural perspective, South Africa is an individualist society as it scores 65 on the Individualism measure on Hofstede's (2001) index; this implies that the market should be less affected by investor sentiment. Taken in conjunction with what has been outlined about the South African economy and stock market, it is likely that the effect of investor sentiment found is driven by economic uncertainty and not necessarily the culture of the country.

Finally, the development of the SA stock market could be the reason behind the role of sentiment. Although there are strong characteristics present in the SA stock market, the factors used to define stock market development would indicate something different. Factors such as income level, gross domestic investment, banking sector development, market liquidity, political risk, law and order and bureaucratic quality are important determinants of a stock market's development (Yartey, 2008). SA has one of the largest Gini coefficients indicating a large gap in income levels; the banking sector is highly developed which is seen to negatively impact stock market development as the one is seen as a substitute for the other as a mechanism for saving and investment; and as mentioned, there is significant political risk in the country. By these standards, it could be said that the SA stock market is relatively underdeveloped and hence is more susceptible to the effects of investor sentiment.

The role interest rates plays in explaining ALSI returns has important implications for traders, particularly foreign exchange traders. A higher interest rate implies that there is more interest accrued on currency invested and therefore traders can earn larger profits. The regression results showed that there was a positive relationship between the interest rate variables and ALSI returns; hence, if traders were to apply the results of the model they would not only gain greater insight into the drivers of market returns but possibly predict the effects on the stock market following an interest rate announcement too. These regression results and trading implications would also be supported by monitoring other economic indicators such as the inflation rate and the unemployment rate. Traders are also able to use the explanatory power of investor sentiment in their predictions; the fact that investor sentiment plays a role in explaining

ALSI returns implies that there is a deviation from fundamentals. As such, traders need to model the deviations from fundamentals to exploit any possible arbitrage possibilities. For policymakers, these results highlight the important point that although interest rate changes are often used to curb inflation in an economy, there are secondary effects on the stock market which need to be monitored as well. The role that investor sentiment plays in explaining ALSI returns also affects policymakers in that the factors which make a country susceptible to the effects of investor sentiment could be addressed through various policy decisions. For South Africa specifically, policies to address the various risks which influence sentiment can be developed to lessen the effects of investor sentiment in the market.

The insights into the South African market and the drivers thereof are broadly consistent with the regression results. The real interest rate, risk premium and term structure variables were found to be statistically significant and positively affect ALSI returns through the company valuation channel for institutions and the saving and consumption channels for individuals. The risk premium also the captures the unique risks of investing in South Africa and should investors receive this additional compensation they will choose to invest, hence there is a positive impact on ALSI returns. Investor sentiment, as measured by FEARS, was also found to be statistically significant and although there are aspects of the South African economy which make it ripe for the effects of investor sentiment, the analysis with the SAVI revealed that the result found could be indicative of noise trading and not necessarily a true statistical relationship. Traders are able to use the results of this regression to better understand and possibly predict the effects on the stock market following an interest rate announcement. Moreover, acknowledgement should be given to the role investor sentiment plays as it causes a deviation from fundamentals. Policymakers, on the other hand, will use this information to ensure their policy decisions have weighed the impact on the greater macro-economy. Furthermore, various factors which influence the magnitude of investor sentiment's impact can also be addressed through policy reform which will have an impact on ALSI return as well.

4.2 Selected G7 Nations

4.2.1 Germany

The regression results in Table 6 above show the two regression models; (1) and (2). Model (1) is the macroeconomic APT without the FEARS variable. This model explains about 49.4% of the variation in DAX returns; the real interest rate, risk premium, and term structure variables were found to be statistically significant at the 5% level of significance. The constant, or intercept, was also found to be statistically significant albeit at the 10% level of significance. The risk premium and real interest rate were found to share a positive relationship with DAX returns; this implies that any increases in these variables would result in an increase in DAX returns. The link between these variables and DAX returns is similar to what has been seen in Brazil, Russia, India, and South Africa. The term structure and intercept variables were found to share a negative relationship with DAX returns; this implies that any increases in these variables would result in a decrease in DAX returns. Model (2) is the macroeconomic APT with the FEARS variable included. This model explains 50.2% of the variation in DAX returns; this is higher than (1) implying that the inclusion of FEARS has improved the overall explanatory power of the model. The real interest rate, risk premium, and term structure variables were all found to be statistically significant at the 5% level of significance. Moreover, in (2) this relationship was found to be positive for all variables; however, the magnitude of the relationship for the real interest rate and risk premium variables appears to have been adversely affected. Surprisingly, the relationship between the term structure and DAX returns is now also positive, where it was negative in (1). Although the inclusion of the FEARS variable improved the explanatory power of the model, the variable itself was found to be statistically insignificant.

As with all the countries, a correlation analysis was done to determine if there are any correlations amongst the variables (Table C6 in Appendix C). There appear to be a number of statistically significant correlations between variables; however, the magnitude of these correlations differ. FEARS is negatively and statistically significantly correlated at the 5% level of significance with DAX returns, industrial production, and the term structure variables. FEARS is also positively and statistically significantly correlated at the 5% level of significance with the real interest rate and risk premium variables. Moreover, the term structure variable is statistically significantly correlated at the 5% level of significance with both the real interest rate and the risk premium. It is likely that a number of the variables in this model are redundant. Through the step-wise regression analysis, it was revealed that the term structure variable is likely to be redundant. Therefore, it appears as though the real interest rate and risk premium variables capture the variation in DAX returns. As such, (2) is viewed as a superior model for explaining the variation in DAX returns.

As an additional check, the correlation analysis between FEARS and the VDAX (Volatility Index) revealed a statistically significant relationship (Output (3), Table C10 in Appendix C) between the two variables. Therefore, the regression and correlation results are congruent in that FEARS does not play an explanatory role in the market.

In trying to reconcile the role interest rates play in Germany, it is important to understand that where other countries struggle with high inflation and hence use the interest rate as a tool to change this, Germany has very low inflation as well as very low interest rates. In an attempt to guard against possible deflation, action has actually been taken to decrease interest rates – essentially Germans are paying to keep their money in banks. This implies that: 1) The value of peoples' savings is decreasing and 2) The value of life insurance policies are being adversely affected as they are achieving much lower yields. It is clear that there are dangers in having low interest rates; however, in Germany interest rates are also being used to influence its inflation. Given the role interest rates play and its impact on the banking and insurance sectors, it would naturally have a large impact on the country's entire financial ecosystem.

The risk premium of a country is based on the level of risk attached to conducting business or investing in that country. Given this, it seems unlikely that the risk premium variable would have statistically significant explanatory power in the German market. Using credit default risk as measure, the Bank of America Merrill Lynch (2015) found that Germany was the least likely to default on its debt. Similarly, the multiple bailouts given to its European neighbours during the Global Financial Crisis are an indicator of the strength and resilience of its stock market as well as its greater economy. Even though there is a small probability of default, the probability still exists and investors still require additional compensation for investing in risky assets – the risk premium variable likely explains this and hence is a statistically significant variable in the German market.

There could be a number of reasons as to why investor sentiment did not explain DAX returns. The first could be that Germany as a country is less susceptible to the effects of investor sentiment, simply due to the nature and strong integrity of their stock market; countries with less market integrity appear to suffer the effects of investor sentiment that much more (Schmeling, 2008). With a strong market regulator, relatively sophisticated investors (Finter, Niessen-Ruenzi, & Ruenzi, 2011), and access to good quality and complete information it is possible that: 1) Investors are able to make informed and timeous decisions for themselves without the influence of others and 2) The strong presence of the regulatory body creates a level of trust inherent in investors. The second reason could be that FEARS simply does not capture investor sentiment in Germany accurately; perhaps an alternative measure of sentiment would yield a different result. In fact, Finter, Niessen-Ruenzi and Ruenzi (2011) construct an index using a variety of investor sentiment measures. Specifically, they employ a German consumer confidence index as a direct measure of sentiment as well as a number of market variables as proxies. The results show that their index had significant explanatory power in explaining the returns in a number of stocks, those that are both sensitive and insensitive to sentiment fluctuations. Finally, the lack of explanatory power of the FEARS could be driven by the culture of German people; Germans have been known to be quite methodical and logical in their thinking and planning which provides them with a much needed sense of security (Goethe Universitat, 2012). This could lend itself to a level of risk aversion in how they conduct business and invest in the stock market. Moreover, research has shown that many investors manage their investment portfolios themselves and spend at least 30 minutes a day reading financial magazines or watching financial news as a means to inform their investment decisions (De Bondt, Zurstassen, & Arzeni, 2001). This provides an indication of the level of sophistication of German investors and hence their likelihood of not behaving in an irrational manner. This implies that they do not behave as emotionally as perhaps other countries do. Moreover, the German culture is a highly individualistic one, scoring 67 on the Individualism dimension in Hofstede's (2001) index. As such, the effect of investor sentiment on such a nation is expected to be small (Schmeling, 2008). The nature and participants in the German stock market, as well as the culture of the nation indicate that investor sentiment might not play as large an explanatory role in Germany as it does in other countries.

The results of the regression as well as an overview of the Germany economy indicate that these results are both statistically and economically significant. The economic significance implies that understanding these results is critical for those participating in the capital market, such as traders, as well as those making policy decisions. The regression results showed that investor sentiment, as measured by FEARS, did not have statistically significant explanatory power for DAX returns. A number of different explanations were offered for this result, specifically the strength of the economy, the culture of the people or that investor sentiment may be better captured using an alternative methodology. Even though investor sentiment played no role in explaining DAX returns, the regression results do provide insight into the Germany stock market and economy.

4.2.2 Japan

The regression results in Table 6 above show the two regression models; (1) and (2). Model (1) is the macroeconomic APT without the FEARS variable. Unfortunately, the Adjusted-R^2 for this model is negative indicating that it lacks explanatory power completely. Consistent with this, no statistically significant variables were found in this model. Model (2) is the macroeconomic APT with the FEARS variable included. This model explains 14.8% of the variation in Nikkei return; this is higher than (1) implying that the inclusion of the FEARS variable has improved the explanatory power of the model. Only the FEARS variable was found to have statistically significant explanatory power, at the 5% level of significance. Furthermore, this relationship was found to be positive which means that any increases in FEARS will result in increases in Nikkei returns. During the construction of the FEARS index it was found that positive economic words had the greatest impact on market returns and hence these were the words included in the index. Therefore, the FEARS index for Japan can be thought of as 'positive' in nature. This explains why an increase in investor sentiment – which is positive in nature – would result in an increase in Nikkei returns; investors are optimistic about their current circumstances which makes them willing to invest, which in turn has a positive impact on Nikkei returns.

The results of the correlation analysis (Table C7 in Appendix C) revealed a number of statistically significant correlations. The term structure and real interest rate variables were found to be negatively and statistically significantly correlated at the 5% level of significance; this is result is similar to what has been observed in other countries. The FEARS index was also found to be positively and statistically significantly correlated with Nikkei returns and the term structure variables at the 5% level of significance. A negative and statistically significant correlation was also found between FEARS and the real interest rate. Although a number of statistically significant correlations were found, the step-wise regression procedure indicated that none of the variables were redundant. Although (2) only has one statistically significant variable, it can be said to be a superior model in explaining the variation in Nikkei returns.

As an additional check, the correlation analysis between FEARS and the Nikkei VIX (Volatility Index) revealed a statistically insignificant relationship (Output (4), Table C10 in Appendix C) between the two variables. Thus, this confirms that FEARS plays an explanatory role in Japan and that the relationship found is true in statistical nature and not caused by noise in the market.

The FEARS index was the only variable which displayed statistically significant explanatory power in the Japanese market; moreover, this relationship is positive. This is expected as the FEARS index was constructed using those words that had the largest impact on returns, which in this case were mostly 'positive' economic words. This implies that when there is an increase in sentiment, largely positive, it translates into action with a positive effect on market returns being observed. In trying to understand why investor sentiment explains returns, it is useful to consider which other behavioural biases Japanese investors suffer from. Research has shown that Japanese investors suffer from overconfidence, short-term bias, and herding. Individual investors tend to suffer from overconfidence, similar to their Chinese peers, as they tend to hold risky stocks, trade too frequently, and buy previous winners making the market susceptible to momentum trading (Kim, Kim, & Nofsinger, 2003). There has been a link made between overconfidence and the level of financial literacy in Japan; the results showed that the higher the investors' financial literacy, the lower their overconfidence bias (Takeda, Takemura, & Kozu, 2013). This provides a solid foundation to combat the overconfidence present in the Japanese stock market – improve investment literacy by enhancing social systems such as investment education. In addition to overconfidence, Japanese investors, similar to most investors, suffer from loss aversion; investors feel more pain from losses than they feel joy from the same amount of gains (Toshimo & Suto, 2004). Behavioural biases are not unique to individual investors; institutional investors tend to suffer from a short-term bias in investment forecasting, herding and evaluating performance relative to one another, and self-marketing to improve the appearance of their portfolio when under pressure (Suto & Toshimo, 2005). The extent of herding behaviour has also been linked to a country's susceptibility to the effects of sentiment; with the effects of investor sentiment being greater in those countries where herding behaviour is common (Schmeling, 2008).

Survey evidence from State Street (2014) provides corroboration for the points highlighted above, as well as provides some additional insights:

- The financial literacy score in Japan is in the 'Failing' bracket and is lower when compared to their Asian peers.
- Japanese investors define investment success as only making gains and no losses; inconsistent with this is that 57% of their portfolio is allocated to cash which has little risk attached to it.

- There is a high degree of risk aversion as Japanese investors become increasingly conservative following losses and will only invest additional savings if markets went up significantly.

Japanese investors, as a whole, appear to suffer from a number of behavioural biases when it comes to financial and investment decision making. A possible explanation could be participation in the stock market which is driven by: 1) The perceived level of risk in the market and 2) Financial literacy. Research has shown that the Japanese market is of a lower quality with respect to both efficiency and fairness when compared to the US (Yano & Komatsubara, 2014). This is clearly reflected if one considers the portfolio allocation of Japanese investors: 57% of their portfolio is allocated to cash, with only 25% being allocated to the equity market in the form of shares (State Street, 2014). Moreover, those who have low financial literacy are significantly less likely to invest in stocks (van Rooij, Lusardi, & Alessie, 2011). Culturally, the Japanese are viewed to be a collectivist society, scoring 46 on the Individualism dimension on Hofstede's (2001) culture index. A lower score on this dimension is often associated with larger effects of investor sentiment (Schmeling, 2008). Overall, Japan's susceptibility to the effects of investor sentiment can be explained by a potential lack of investment literacy, the prevalence of several behavioural and psychological biases, and its collectivist culture.

The results of the regression as well as some insight into Japanese investors indicate that these results are likely to be both statistically and economically significant. The regression results showed that investor sentiment, as measured by FEARS, was a statistically significant explanatory variable. There are a number of reasons offered as to why this could be the case – overconfidence, a possible lack of investment literacy, and a level of risk aversion. Logically, however, if an investor lacks investment literacy there will be a higher reliance on behavioural and psychological biases when making financial decisions; this could very well be the case for Japanese investors. The regression results and accompanying analysis about the Japanese market and its investors has yielded great insight.

Attention should also be paid to the fact that the sample size of the Japan analysis was limited compared to most of the other countries under examination.

4.2.3 United Kingdom

The regression results in Table 6 above show the two regression models; (1) and (2). Model (1) is the macroeconomic APT model without the FEARS variable. This model explains 0% of the variation in FTSE returns; moreover, no variables were found to be statistically significant. Model (2) is the macroeconomic APT model with the inclusion of the FEARS variable. This model explains 31.1% of the variation in FTSE returns; this is higher than (1) implying that that including the FEARS variable increases the explanatory power of the model. The industrial production and FEARS variables were found to be statistically significant at the 5% level of significance. The relationship between industrial production and FTSE returns was found to be positive which indicates that any increases in industrial production will result in increases in FTSE returns. Conversely, the relationship between FEARS and FTSE returns was found to be negative, implying that any increases in FEARS will result in decreases in FTSE returns. This inverse relation is explained by the construction of the FEARS index for the UK; during the construction process is was found that negative words play the largest role in explaining FTSE returns and hence those were the words included in the index. As such, the FEARS variable can be said to be 'negative' in nature and hence any increases in negativity would result in an adverse effect on FTSE returns.

The results of the correlation analysis (Table C8 in Appendix C) indicate that although there were a number of statistically significant correlations between variables, there are no redundant variables present. The industrial production variable was found to be correlated with all variables, barring the FEARS index, at the 5% level of significance; this could possibly reiterate the role industrial production plays in the UK economy. Its strongest correlation, however, was with the inflation variable which is expected due to both variables capturing the rising price of goods. The term structure and risk premium variables were found to be negatively and statistically significantly correlated at the 5% level of significance; this is likely due to the relationship both variables share with the government bond return. Given the analysis, it would appear that the variation in FTSE returns is best captured by (2).

As an additional check, the correlation analysis between FEARS and the FTSE VIX (Volatility Index) revealed a statistically significant relationship (Output (5), Table C10 in Appendix C) between the two variables. Thus, although FEARS was found to be statistically significant, the correlation analysis finds that this relationship could be driven by noise in the market rather than a true statistical relationship.

The negative relationship found between FEARS and FTSE returns was small in magnitude, but the direction is logically explained; the FEARS index was constructed using words which, when tested, had a large negative impact on returns. As such, any increases in sentiment (which is essentially negative) will result in adverse effects on the stock market. When investors are pessimistic about the stock market, they turn to alternative investment or savings mechanisms which, in turn negatively affects the stock market and the associated returns. The UK market is seen as quite a sophisticated and mature stock market with strong regulatory oversight; this begs the question of why UK investors are behaving in an irrational manner? There is evidence that both answers and refutes that specific question. In answering why UK investors behave irrationally, research has shown that UK investors have a clear understanding of the risk-return relationship; however many were not clear about what those risks actually were and took a short-term view to investing as long-term investing meant they could not access their capital. There is also a low level of knowledge and understanding of investment products and many investors tend to be risk averse (Collard, 2009). A lack of understanding implies that instead of making logical and rational decisions, UK investors make irrational ones as they cannot process financial information and make an informed decision. As a result, they may be more driven by sentiment than logic and sound reasoning. Conversely, there is evidence to show that the UK investor is in fact a sophisticated one. Research has shown that UK investors are highly risk tolerant and patient investors (Hens, Rieger, & Wang, 2015) who manage their own investment portfolios and spend time gathering financial information from various sources to inform their investment decisions (De Bondt, Zurstassen, & Arzeni, 2001). This implies that they are willing to accept a level of risk provided it is a calculated one which has been informed by the processing of financial information. Culturally, the UK is even more individualistic than Germany. The UK scored 87 on the Individualism dimension of Hofstede's (2001) culture index. In an instance such as this one, the effects of investor sentiment on market returns is expected to be small (Schmeling, 2008). The opposing hypotheses, taken in conjunction with the relationship found between FEARS and FTSE VIX as well as the cultural angle, indicate that perhaps noise trading is the reason behind the result.

The regression results and insight provided into the UK market indicate that these results are both statistically and economically significant. The regression results showed that investor sentiment, as measured by FEARS, had explanatory power for FTSE returns. There is evidence that investors in the UK can behave both rationally and irrationally, and given the results of the FEARS and FTSE VIX correlation analysis it would appear that noise trading could be present.

Despite this, the regression results and discussion has provided keen insight into the UK stock market and economy.

4.2.4 United States

The regression results in Table 6 above show the two regression models; (1) and (2). Model (1) is the macroeconomic APT without the FEARS variable. This model explains 23.5% of the variation in S&P500 returns; unfortunately only the intercept was found to be statistically significant at the 5% level of significance. Model (2) is the macroeconomic APT with the inclusion of the FEARS variable. This model explains 33.6% of the variation in S&P500 returns; this is higher than (1) implying that the inclusion of the FEARS variable has increased the explanatory power of the model. Similar to (1), the intercept was found to be statistically significant at the 5% level of significance. Moreover, investor sentiment, as measured by FEARS, was also found to be statistically significant at the 5% level of significance. This relationship was also found to be negative in nature – this is as a result of the index construction process. When determining the words to be included, the regression revealed that negative economic words had the greatest impact on market returns and hence those were the words that were included. As such, it could be said that the FEARS index for the United States measures 'negative' sentiment. This explains why an increase in investor sentiment has a negative impact on S&P500 returns; investors are pessimistic about the current state which is captured in the search volume data for each word.

The results of correlation analysis (Table C9 in Appendix C) show that there are a number of statistically significant correlations. Specifically, the term structure variable was found to be negatively and statistically significantly correlated to both the real interest rate and term structure variables at the 5% level of significance. This is similar to what has been observed in other countries as these variables are related to each other through the government bond return. FEARS and the risk premium variables were also found to be negatively and statistically correlated to the S&P500 return series at the 5% level of significance. The step-wise regression procedure indicated that the risk premium variable, although not statistically significant, is likely to be redundant. The analysis indicates that (2) is the superior model for explaining the variation in S&P500 returns and investor sentiment plays a statistically significant and explanatory role in this.

As an additional check, the correlation analysis between FEARS and the S&P500 VIX (Volatility Index) revealed a statistically significant relationship (Output (6), Table C10 in Appendix C) between the two variables. Thus, although FEARS was found to be statistically significant, the correlation analysis finds that this relationship could be driven by noise in the market rather than a true statistical relationship.

The results of the US regression model can be broadly compared to the results found by Chen, Roll, and Ross (1986). The authors found that industrial production, changes in the risk premium and the term structure of rates have significant power in explaining stock returns. These results do no correlate with those found in regression model (2) as only the intercept was found to be statistically significant. The differences in result could be due to the difference between the data sources used, as well as the time period for each study. As surprising as this result is, this study is not the first to find no statistically significant relationship between numerous macroeconomic variables and the S&P 500 – Fitzpatrick (1994) had a similar outcome. In terms of the variables utilised, Fitzpatrick (1994) focused on growth in corporate earnings, gross national product, money supply, CPI, 3 month Treasury bill, and the treasury composite. Although there is some overlap in the variables used, the main outcome was similar – no significant relationship could be found between macroeconomic variables and the S&P 500 index.

The negative relationship between FEARS and market returns can be explained based on how the FEARS index was constructed. Although the initial word list included both positive and negative economic words, only those which have the largest impact on returns were included. For the US this happened to be words that had strong and negative relationships with market returns. Hence any increases in FEARS sentiment – largely negative – would have a negative impact on the market as investors would be averse to investing when sentiment is low. The effects of investor sentiment in the US have been widely studied and the literature has shown that investor sentiment, especially in the US, can be measured using a variety of measures. This indicates that investor sentiment research in the US is far more advanced than a number of the other countries examined in this study. This raises questions about the country's susceptibility to the effects of investor sentiment.

Hens, Rieger, and Wang (2015) conducted research into the psychology of investing in various countries around the world. US investors were found to be willing to pay more for equities than investors in European countries; implying that US investors are more risk tolerant than their

European counterparts. Interestingly, the US was found to have more “Ego-Traders” than elsewhere; the US was found to be more individualistic which drives a culture of seeking quick gains and having very little patience when it comes to making financial decisions. This implies that once information has been received, regardless of the source, very little time is given to properly analysing data to understand its financial implication. Instead, it appears as though decisions are made very quickly to avoid losing out on any potential financial gains. Stock market participation is also a function of trust in the market and its regulatory bodies, which American investors seem to lack (Guiso, Sapienza, & Zingales, 2008). Investors fear being cheated by other capital market participants, this is particularly so with wealthy investors which affects the inflow of capital into the economy. A lack of trust coupled with impatience in making financial decisions may result in a reliance on the so-called ‘rumour-mill’ to fuel investment decisions which results in a momentum-driven economy. Support for the presence of momentum in the market can be provided by understanding the link between a highly individualistic society, such as the US, and the magnitude of momentum profits. The US was found to be highly individualistic through Hofstede’s (2001) culture index, scoring 91 on the dimension. Moreover, individualism was found to be positively associated with magnitude of momentum profits (Chui, Titman, & John Wei, 2010). The individualistic nature of US investors causes them to be highly susceptible to multiple cognitive and psychological biases, making the country more susceptible to the effects of investor sentiment.

The results of the regression as well as some insight into American investors indicate that these results are likely to be both statistically and economically significant. The regression results showed that investor sentiment, as measured by FEARS, was a statistically significant explanatory variable. There are a number of reasons offered as to why this could be the case – the level of risk aversion of US investors which drives irrational decisions, a lack of trust in the market, its participants and its regulatory bodies, and a possible reliance on the rumour-mill to inform financial decisions. Moreover, the relationship found between FEARS and S&P500 returns could be as a result of noise trading and hence not indicative of a true statistical relationship. That being said, the regression analysis and information about the US market has definitely yielded insight into the market and the market participants.

4.3 Discussion of Results

Upon considering the results of all the countries above, it becomes clear that there are several key outcomes and implications which emerge from this study's results.

The first of these being that different macroeconomic variables can be used to explain a country's returns; this is based on what is driving that country's stock market as well as its economy as a whole. There were some consistencies between countries – risk premium, term structure and real interest rate were found to have explanatory power in five out of the nine countries. Other variables such as inflation and industrial production also demonstrated explanatory power in certain countries. With regards to the number of variables found to be statistically significant, these results are consistent with those uncovered by Chen, Roll, and Ross (1986) – three strong explanatory variables and a fourth slightly weaker variable.

Moreover, many of the relationships found are not only statistically significant but economically significant as well. The statistical relationship found between a specific variable and a country's stock market can be explained using macroeconomic theory. In a number of countries, the term structure and real interest rate variables were found to be statistically significant. This has economic significance as this relationship can be explained by exploring both the institutional as well as individual effects. Company valuations, using the discounted cash flow methodology, will be affected by changes in interest rates which will in turn affect a firm's stock price. Seeing that interest rates are a macroeconomic lever a country's central bank will pull, it is likely that many companies' valuations will be affected. As a result, the indices which represent a country's stock market will also be affected. A change in interest rates will also serve to change consumer spending behaviour. For example, higher interest rates will encourage consumers to save rather than spend, as the interest rates on deposit accounts or investments will be higher. As such, there will be an inflow of money into financial instruments of various types, where previously the money was flowing into the economy in the form of consumption.

The risk premium was also found to be a statistically significant explanatory variable in multiple countries. The reason for this lies in what exactly a risk premium captures; the risk premium is a form of compensation offered to investors for investing in risky assets. The positive relationship found between the risk premium and a country's market return captures an investor's behaviour when this risk premium is on offer; when an investor has the opportunity to receive additional compensation for investing in an asset, the investor will choose to do so. Consequently, the investor opts to invest in the asset which has a positive impact on market returns.

Russia was the only country where inflation appeared to have statistically significant explanatory power for the country's market returns. Inflation is an important factor in the development of a stock market (Vasiliev, 2010) and a low inflation rate is indicative of macroeconomic stability (Yartey, 2008). Russia's inflation rate, however, is extremely high which indicates a level of macroeconomic instability in the country. Their historically high inflation rates have been crippling to the economy and have not yet stabilised to the point where it encourages economic development. The positive relationship between inflation and Micex returns found is also inconsistent with what theory dictates in the short-term – high inflation rates reduce an individual's purchasing power, this actually has a negative impact on stock prices as investors require a higher rate of return as part of the return is being eroded by the higher inflation rate. In the longer term, however, the additional costs are passed to consumers and hence stock prices will tend to increase in line with the inflation rate. A further explanation is that during periods of rising inflation, a country's central bank will often increase interest rates to curb this increase. This also serves to attract investors to save their cash in fixed income instruments, so there is actually an inflow of capital into the stock market

Furthermore, China was the only country where the oil price displayed statistically significant explanatory power for the country's market returns. There is some evidence to indicate that oil price shocks do have an impact on market returns in China (Broadstock & Fillis, 2014; Yun & Yoon, 2015). The economic significance of this relationship, however, is interesting as it stems from the building blocks of the Chinese economy. The oil sector plays an important role in China's economy and has also been the focus of major structural reforms and high-level attention from the government. Despite the policy reforms towards more market-oriented oil sector, government ownership, limited foreign investment, and inefficient expansion strategies still characterise the industry. Since 1979, China's demand for oil has surpassed its oil production which has resulted in China becoming one of the top importers of oil in the world. The magnitude of China's demand for oil has dire implications, as their influence on and vulnerability to the international oil market is significant. Moreover, this discrepancy between demand and domestic supply is only getting larger, leaving China with tough choices to conquer their energy crisis (Soligo & Jaffe, 2004). China's history with oil as well as the challenges it will face going forward provides an explanation of why the oil price may affect the performance of the country's stock market.

Finally, industrial production was found to play a statistically significant explanatory role in only one market, the UK. The explanation behind this result can be found in the history of the British economy. A major contributor to the development of the UK economy dates back to the Industrial Revolution, as well access to natural resources used for both domestic use as well as international trade. This resulted in industrial innovations that surpassed other countries; the UK became the first nation in the world to industrialise its economy (Lohia, 2013). As the first movers, the UK economy experienced substantial growth which has catapulted them into being considered one of the largest economies in the world. Its economy is primarily driven by the services industry; financial and professional services (76.9%), industrial sector (19.7%), agriculture (0.6%) (CIA World Fact Book, 2015). As such it is expected that, given its history and how that has been translated into revenue, that industrial production would have a positive impact on market returns in the UK.

It has been shown that the results uncovered in this study are both statistically and economically significant. Their economic significance implies that these results can be used by various stakeholders to fuel their decisions. These results would be of particular significance to traders and policy decision makers. The regression results revealed that the term structure of rates, real interest rate, risk premium, inflation, industrial production and the oil price have statistically significant explanatory power in various countries. This implies that a trader, using this information, would be in a position to predict future market movements given changes in any of these variables. Ultimately, these results would allow a trader to maximise their potential trading profits. It is also critical to remember that these variables do not act in isolation in a country's economy; it is the interconnections between these variables which also present traders with the opportunity to time the market. In addition to implications for traders, these results also have implications for those in policy decision making positions. These results provide insight to such individuals as to the key drivers of a particular country; although a number of similarities were found, some key differences were found too likely driven each individual country's history and development. These results would provide policy decision makers with a holistic view of the aspects which could affect their country's economy; which will allow them to plan and draft policy accordingly. It will ensure that policy is drafted with the country's best interests in mind as these policy decisions could go beyond the stock market and could extend to the overall economy, the judicial system as well as regulatory bodies. Given the history and current state of some of the countries explored in this study, fair and well-thought out policy would encourage strong and sustainable economic growth.

Identification of these country-specific policy implications was made possible purely by the international nature of this study as it allowed for a greater understanding of various international markets.

The second outcome is around the measurement of investor sentiment. The literature section outlined the numerous methodologies available for one to measure investor sentiment, with each measure capturing something different. Using Google data as a source for investor sentiment relies on a number of factors, including but not limited to: 1) High levels of Internet usage in the country; 2) User activities on the Internet; and 3) The use of Google as a search engine. To the first point, Internet usage has been on an increasing trend in most countries especially as accessibility improves and technology progresses. The specific activities of a user on the Internet will also affect the data compiled by Google Trends; if users in one country use the Internet more for transacting as opposed information gathering then this would influence the search volume data of the economic words chosen. Furthermore, the choice of search engine is entirely a personal preference for many; the only anomaly in this case was China as Google is one of the numerous websites banned in the country (this ban applies to mainland China only and excludes Hong Kong and Macau). As such, it may be the case that investor sentiment in China can be better explained using an alternative measure, perhaps market variables. Similarly, this could be case for any of the countries where FEARS was not found to have any statistical significance. Nevertheless, FEARS was found to have explanatory power in five out of the nine countries, specifically Russia, SA, Japan, UK, and the US. A final point regarding the measurement of investor sentiment relates to the fundamental construction of the FEARS index. In their study, Da, Engelberg and Gao (2015) found that, despite including both 'positive' and 'negative' economic words, the strongest relationship found between a search word and the market was found to be negative in nature. This provides support for literature which posits that negative words tend to be more effective in identifying sentiment (Tetlock, 2007). The same result was uncovered in this study, albeit for six out of the nine countries. Contrary to what is expected, this relationship was found to be positive in nature for the remaining three countries (Russia, China and Japan). This finding highlights that each country's stock market has its own unique drivers and that both positive and negative sentiment can be captured using search data.

Finally, no clear link could be made between the classification of a country (developed versus developing) and the explanatory power of investor sentiment in that country. In the BRICS countries, Russia and SA were the only two countries where FEARS played an explanatory role in the stock market. Similarly out of the G7 countries chosen, FEARS had explanatory power in three out of the four countries – specifically in Japan, UK and the US. Even though this distinction could not be made, there are other characteristics of a countries' economy which could influence its susceptibility to the effects of investor sentiment such as, the country's economic and political climate and stability, the level of trust investors have in the stock market and its regulatory bodies, the level of access and quality of information available, and individual investor behaviour.

Overall, the results are a mix between whether investor sentiment, as measured by the FEARS index, as an APT factor is feasible in explaining returns. In five out of the nine countries examined, it can be concluded that there is statistically significant explanatory power of the investor sentiment factor. Unfortunately, for the remaining four countries this is not the case. Overall, it would be useful to increase the sample to include other countries to have a clear indication of investor sentiment's explanatory power as an APT factor. Nevertheless, the results address both the problem as well as the objective outlined; the statistical testing demonstrated the explanatory power, or lack thereof, of various factors in the APT, including investor sentiment.

China remains an anomaly as Google is one of the websites China has banned (this ban applied to the mainland only as it excludes Hong Kong and Macau). For the remaining countries, consideration must be given to the fact that investor sentiment could be better captured and measured using an alternative method or alternatively, the country itself is not as susceptible to the effects of investor sentiment as others are. These results have confirmed that a measure of macroeconomic investor sentiment has a role in explaining asset prices and their associated returns; this makes a valuable contribution to the existing literature on the APT and which factors can be used under this framework. The results have also confirmed that three to four factors is the optimal number when deciding on how many factors to include under the APT framework. The results also add to the existing literature on the individual countries, specifically with regards to the macroeconomic drivers of the country and its stock market.

As an aside, these results have provided insight into the inner workings of a country's economy and stock market as well as allowed for comparisons across countries. This was made possible by the individual APT models created for each country and would not have been possible if an IAPT was created for BRICS and the G7 countries as it would not have had the level of detail incorporated into each country's APT models.

5 Conclusion

Asset pricing can be broadly defined as a collection of theories whose aim is to determine the fair price of an asset. Moreover, there is a close relationship between the fundamental value of an asset and the appropriate return that asset should earn. It is important to note the difference between the fundamental value of an asset and the price of the asset as it is observed in the market. Generally, theories tend to be focused more on the fundamental value of an asset; whereas asset pricing theories, such as the APT, are widely used to explain observed or market prices. The understanding of asset prices and returns is fundamental to an economy as it affects asset allocation, the allocation of resources, the measurement and management of financial risks, and influences individuals' decision making on a daily basis; as such, it is critical that, using asset pricing, a more thorough understanding of the risk-return relationship is gained.

Traditional finance theory surrounding the risk-return relationship is underpinned by the CAPM which posits that a single risk factor, specifically market risk, is priced into asset returns. The CAPM has been widely criticised due to its unrealistic assumptions and the APT was developed to address the CAPM's weaknesses. The most significant difference between the two models is that the APT allows for a multitude of risk factors to be priced into asset returns. This implies that the APT framework can be used to model returns using either macroeconomic or microeconomic factors. As such, the APT allows for non-traditional factors, such as investor sentiment, to be included. A macroeconomic APT framework was used as the base for this study; a framework was developed for nine countries – Brazil, Russia, India, China, South Africa, Germany, Japan, the United Kingdom, and the United States – using the variables outlined by Chen, Roll, and Ross (1986). Thereafter, an investor sentiment variable was included, specifically the FEARS index created by Da, Engelberg and Gao (2015) . The FEARS index is constructed for each country using the search volume data from Google Trends for a specific list of positive and negative economic words. As such, this index reflects the household economic sentiment of a specific country. Regression testing was employed to test the hypothesis of whether FEARS, or rather investor sentiment, is a statistically significant explanatory variable in the APT models for the respective countries.

The results show that different macroeconomic variables explain the returns in different countries. The variables which had explanatory power in multiple countries include the real interest rate, risk premium, and term structure of rates. Variables such as inflation, industrial production, and the oil price had explanatory power, albeit in few countries. All the variables found to be statistically significant throughout the analysis were also found to be economically significant as these variables play a critical role in a well-functioning economy. The inclusion of the FEARS index as an explanatory variable into the regression had mixed results. In some cases, it improved the explanatory power of the regression model and in some cases it did not. Moreover, the improvement on the model also varied in magnitude across the countries. The FEARS index had statistically significant explanatory power in five out of the nine countries under examination; specifically, Russia, South Africa, Japan, the UK, and the US. This implies that, in these countries, investor sentiment can be used as a factor in explaining market returns and hence the hypotheses outlined previously do hold in each of these five countries. Specifically, in Russia and Japan investor sentiment was found to have a positive relationship with stock market returns – potentially driven by the fact that each country's FEARS index was 'positive' in nature. Whereas in South Africa, the UK and the US the relationship between investor sentiment and market returns was found to be negative – this could also be driven by the fact that each country's FEARS index was 'negative' in nature. For the remaining countries – Brazil, India, China, and Germany – FEARS did not appear to have any statistical significance in explaining market returns. This implies that, in these countries, investor sentiment cannot be used to explain market returns and hence the hypotheses outlined previously do not hold in each of these four countries. Given that investor sentiment was found to be statistically significant in five out of the nine countries examined, the primary hypothesis can be declared valid for these five countries, based on the assessment criteria outlined previously. As such, it can be said that investor sentiment, as an APT factor, is feasible in explaining returns in five out of the nine countries examined. Unfortunately, no statistically significant relationship was found in the remaining four countries. Overall, it would be useful to increase the sample to include other countries to have a clear indication of investor sentiment's explanatory power as an APT factor. Finally, no clear link could be established between the classification of a country as developed or developing and the explanatory power of investor sentiment.

Despite a mix in the statistical significance of the results, it is clear that the study and its results addressed the problem and objectives outlined in Section 1.1. The problem facing many existing and traditional asset pricing models is that they are grounded in an assumption of a completely rational investor. Asset pricing models do not take into account the effect an irrational investor could have on explaining market returns. Considering investor sentiment, measured by the FEARS index, as a factor in an APT model will provide great insight into the effect that investors' thoughts and beliefs may have on determining market returns. Hence, the objective is to determine whether investor sentiment has explanatory power for market returns in various countries around the world. More generally, however, the objective is the feasibility of various APT factors, including investor sentiment, in explaining market returns and not the creation of an APT model. The results of the statistical testing demonstrated investor sentiment's explanatory power, or lack thereof, in the countries under examination, thereby addressing the objective of this study.

The results yielded in this study add to the body of literature on the APT as well as country-specific literature. It was found that investor sentiment is a statistically significant in explaining asset prices and their associated returns, in various countries. Additionally, in alignment with previous literature, it was found that three to four factors are optimal when using the APT framework to explain asset prices and returns. As such, this study contributes to APT literature by confirming the explanatory power of investor sentiment in the market as well as support for research into the optimal number of factors under the APT framework. In seeking an explanation for these results, the individual nuances of the countries under examination were highlighted; this provided great insight into the countries themselves as well as provided an understanding of the individual drivers of a given country's macro-economy and stock market.

These results also have trading and policy implications. For traders, the ability to understand the effect that macroeconomic variables have on the stock market as well as the role investor sentiment may play in a country enables the trader to predict any possible changes and hence maximise profits. For example, the real interest rate, risk premium and term structure of rates variables were found to be statistically significant in numerous countries. The statistically significant relationship found between these variables and stock market returns could be exploited by traders in their trading activities. The policy implications would be different for each country; however these results could influence economic, stock market, judicial and regulatory decisions. Moreover, policy decision makers could use these results to ensure that they are developing policy which is holistic, considers all potential impacts, and is in the best interests of the country. For example, in countries that were found to be more susceptible to the effects of investor sentiment, policies can be drafted to improve the robustness of regulatory bodies such that it encourages a level of trust from investors that any wrong doing will be rectified correctly. A greater level of trust in the stock market and its operations implies that: 1) Investors will feel more secure in investing on the stock market, which have a positive impact on the stock market and 2) The quality of investment decisions made by investors will improve, theoretically weakening the effects of investor sentiment on the stock market. A further example is designing monetary policy such that it does not have a negative impact on the stock market, but is still in the best interest of the consumer.

This study has yielded insight into the individual intricacies of the economies and stock markets of the countries examined; these insights have then further been applied to both the trading and policy making environments. Ultimately, this study was able to provide a greater understanding of the drivers of a country's economy and stock market, which was made possible by the individual APT models constructed for each country. This level of insight would not have been achieved under the IAPT; the ambiguity of the empirical testing would have highlighted more questions to be answered as opposed to providing insight into the individual countries.

An unfortunate delimitation to this study is the data sampling. This is regarded as a limitation for two reasons. Firstly, the sample size was relatively small due to the data availability; however, should alternative data sources be found – particularly the high yield bond index used to calculate the risk premium – then the sample size could be increased. Secondly, the sample periods were not consistent across countries; this makes direct comparability between countries an issue. Once again, this was driven by the availability of data sources and should be remedied with alternative data sources. A further delimitation lies in the international nature of this study; the oil price for each country was denominated in each country's respective currency which opens the door for possible exchange rate risk.

5.1 Considerations for Further Research

An interesting extension to this study would be to conduct further research to consider the concept of volatility spill over or the contagion effect between countries. Volatility spill over, or the contagion effect, refers to the fact that the volatility experienced in a given market could be explained by events taking place in other countries (Bekaert & Harvey, 1997). Investor sentiment is not a factor that is often captured in return processes, whether the CAPM or APT, so its effects would likely be captured in the error term of the model, assuming sentiment to play a role in the returns generating process. Without the investor sentiment factor, the effects of good or bad news shocks in these models have to be modelled using volatility spill over models, such as the ARCH (Autoregressive Conditional Heteroscedastic) family of models. This could provide explanation into two important aspects of financial markets:

1. If an investor sentiment factor is included in the model from the outset it could negate the need to run specific volatility spill over models, as well as provide an indication of how news shocks in one country affects other countries.
2. Much of the existing literature declares the US to be the economic powerhouse of the world, driving a large part of economic and financial movements. However, Asian markets such as China and Japan have been gaining traction at rapid rates. It would be interesting to see if there has been a shift in the economic and financial powerhouses of the world, from the US to either, China or Japan.

The international nature of this study allows for a cultural lens to be applied in understanding why investor sentiment has explanatory power in some countries and not in others. The body of evidence to support this is relatively new; however, it has proven that culture can affect economics and finance in a number of ways and may provide further insight into why investor sentiment plays an explanatory role in some countries and not in others.

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Appendix A

Table A1: Description of Data Sets Used

Country	Variable	Data Set	Abbreviation	Frequency	Source
All	Investor Sentiment – FEARS	Google SVI	FEARS	Weekly/Monthly	Google Trends
Brazil	Market Index	Bovespa	IBOV	Monthly	Bloomberg
	Risk Free Rate	1 year government bond	RF	Monthly	Bloomberg
	Long-term Government Bond	10 year government bond	LTB	Monthly	Bloomberg
	Inflation	National Consumer Price Index	INF	Monthly	Brazil Institute of Geography and Statistics
	Industrial Production	Industrial Production	IP	Monthly	
	Return on high yield bonds	Bloomberg High Yield Emerging Market Corporate Bond Index	BEAC	Monthly	Bloomberg
	Oil Price	Oil price	BOP	Monthly	World Bank
Russia	Market Index	MICEX	MICEX	Monthly	Bloomberg
	Risk Free Rate	1 year government bond	RF	Monthly	Bloomberg
	Long-term Government Bond	10 year government bond	LTB	Monthly	Bloomberg
	Inflation	Inflation	INF	Monthly	Russian State Statistics Service

	Industrial Production	Domestic PPI	IP	Monthly	Federal Reserve Bank of St. Louis
	Return on high yield bonds	Bloomberg High Yield Emerging Market Corporate Bond Index	BEAC	Monthly	Bloomberg
	Oil Price	Oil price	ROP	Monthly	World Bank
India	Market Index	Nifty	Nifty	Monthly	Bloomberg
	Risk Free Rate	1 year government bond	RF	Monthly	Bloomberg
	Long-term Government Bond	10 year government bond	LTB	Monthly	Bloomberg
	Inflation	Inflation	INF	Monthly	Bureau of Labour Statistics
	Industrial Production	Producer Price Index	IP	Monthly	Ministry of Statistics, Government of India
	Return on high yield bonds	Bloomberg High Yield Emerging Market Corporate Bond Index	BEAC	Monthly	Bloomberg
	Oil Price	Oil price	IOP	Monthly	World Bank
China	Market Index	Shanghai SE Composite Index	SSE	Monthly	Bloomberg
	Risk Free Rate	1 year government bond	RF	Monthly	Bloomberg
	Long-term Government Bond	10 year government bond	LTB	Monthly	Bloomberg
	Inflation	Consumer Price Index	INF	Monthly	

	Industrial Production	Producer Price Index	IP	Monthly	National Bureau of Statistics of China
	Return on high yield bonds	Barclays Asia High Yield Bond Index	AHYG	Monthly	Bloomberg
	Oil Price	Oil price	COP	Monthly	World Bank
South Africa	Market Index	All Share Index	ALSI	Monthly	JSE
	Risk Free Rate	3 month government bond	RF	Monthly	SA Reserve Bank
	Long-term Government Bond	10 year government bond	LTB	Monthly	Bloomberg
	Inflation	Consumer Price Index	INF	Monthly	StatsSA
	Industrial Production	Producer Price Index	IP	Monthly	Bureau of Economic Research
	Return on high yield bonds	Bloomberg High Yield Emerging Market Corporate Bond Index	BEAC	Monthly	Bloomberg
	Oil Price	Oil price	SOP	Monthly	World Bank
Germany	Market Index	Deutscher Aktienindex	DAX	Monthly	Bloomberg
	Risk Free Rate	1 year government bond	RF	Monthly	Bloomberg
	Long-term Government Bond	10 year government bond	LTB	Monthly	Bloomberg
	Inflation	Inflation	IN	Monthly	German Statistics Office
	Industrial Production	PPI	IP	Monthly	

	Return on high yield bonds	Bloomberg Euro High Yield Corporate Bond Index	BEUH	Monthly	Bloomberg
	Oil Price	Oil price	GOP	Monthly	World Bank
Japan	Market Index	Nikkei 225	Nikkei	Monthly	Bloomberg
	Risk Free Rate	1 year government bond	RF	Monthly	Bloomberg
	Long-term Government Bond	10 year government bond	LTB	Monthly	Bloomberg
	Inflation	Consumer Price Index	IN	Monthly	Japan Statistics Bureau
	Industrial Production	Industrial Production	IP	Monthly	Ministry of Economy, Trade and Industry
	Return on high yield bonds	Barclays Asia High Yield Bond Index	AHYG	Monthly	Bloomberg
	Oil Price	Oil price	JOP	Monthly	World Bank
United Kingdom	Market Index	FTSE 100	FTSE	Monthly	Bloomberg
	Risk Free Rate	1 year government bond	RF	Monthly	Bloomberg
	Long-term Government Bond	10 year government bond	LTB	Monthly	Bloomberg
	Inflation	Inflation	IN	Monthly	Office for National Statistics
	Industrial Production	Producer Price Index	IP	Monthly	Eurostat

	Return on high yield bonds	Bloomberg Pound High Yield Corporate Bond Index	BGBH	Monthly	Bloomberg
	Oil Price	Oil price	UKOP	Monthly	World Bank
United States	Market Index	Standard & Poor's 500	S&P 500	Monthly	Bloomberg
	Risk Free Rate	1 year government bond	RF	Monthly	Bloomberg
	Long-term Government Bond	10 year government bond	LTB	Monthly	Bloomberg
	Inflation	Consumer Price Index	INF	Monthly	US Bureau of Labour Statistics
	Industrial Production	Industrial Production	IP	Monthly	Federal Reserve Bank of St. Louis
	Return on high yield bonds	Bloomberg Dollar High Yield Corporate Bond Index	BUHY	Monthly	Bloomberg
	Oil Price	Oil price	USOP	Monthly	World Bank

Appendix B

This appendix outlines the top thirty search words that were used in the construction of the FEARS index per country. Given that the selection of words was informed by a regression analysis to test which words have the largest impact on market returns, the words differ across the various countries.

Table B1: Top Thirty Words per Country used in FEARS Construction - BRICS

Brazil	Russia	India	China	SA
Luxury	Allowance	Laid	Fine	Steal
Treasure	Equity	Community	Tax	Bonus
Prosperity	Inherit	Business Cycle	Private Equity	Hustle
Pension	Skill	Fire	Price	Gold Price
Stock	Fire	Competitive Advantage	Pension	Inexpensive
Ruin	Contribution	Colony	Cheap	Treasure
Ghetto	Radical	Nobility	Compensation	Reward
Bonus	Hustler	Waste	Radical	Broke
Boom	Legal	Inflation	Segregation	Charity
Radical	Gamble	Depression	Inherit	Donation
Partner	Patron	Gold Price	Bargain	Partner
Cost	Gain	Stagflation	Security	Riches
Economise	War	Endowment	Cooperative	Allowance
Colony	Domination	Reward	Community	Ghetto

Poor	Money	Backward	Partner	Colony
Cheap	Ruin	Benevolent	Contribution	Expense
Debt	Cost	Limited Partnership	Worth	Bum
Apartheid	Donation	Gold	Gift	Savings
Backward	Cooperative	Poverty Reduction	Buy	Lay
Corrupt	Buy	Success	Guide	Inherit
Crisis	Debt	Poor	Foundation	Rich
Charity	Depression	Savings	Stock	Philanthropy
Race	Reward	Unemployment	Thrift	Hole
Private Equity	Ghetto	Cooperative	Partnership	Backward
Capitalise	Treasure	Aristocrat	Inheritance	Competitive Advantage
Default	Luxury	Hole	Broke	Blackmail
Gold Price	Tariff	Apartheid	Abundance	Racism
Inherit	Compensation	Partnership	Default	Deficit
Waste	Worth	Broke	Depreciation	Bargain
Hole	Bargain	Skill	Laid	Expensive

Table B2: Top Thirty Words per Country used in FEARS Construction - G7 Nations

Germany	Japan	UK	US
Charity	Recession	Entrepreneurial	Racial Segregation
Bonus	Inflation	Bequeath	Cheap
Foundation	Success	Vagrant	Accrue
Recession	Reward	Abundance	Affluence
Community	Skill	Hustler	Incentive
Domination	Tariff	Invaluable	Frugal
Allowance	Bargain	Guide	Government Budget Balance
Deficit Spending	Unemployment	Apartheid	Market Liquidity
Skill	Productivity	Bonus	Allowance
Capitalise	Rich	Generosity	Prosperous
Prosperity	Abundance	Affluent	Lobbying
Hole	Partner	Accrue	Profit
Extravagant	Gamble	Hustle	Public Private Partnership
Waste	Foundation	Profitable	Liquidate
Great Depression	Charity	Liquidate	Charitable
Riches	Laid	Treasure	Hyperinflation
Savings	Legal	Worker Compensation	Backer
Success	Bribery	Segregation	Race
Nobility	Beneficiary	Benevolent	European Debt Crisis

Vagabond	Worth	Expensive	Bankruptcy
Gamble	Hustle	Frugal	Beggar
Poverty	Thrift	Allowance	Hustler
Corrupt	Afloat	Luxury	Productivity
Liquidation	Steal	Partner	Savings Loan Crisis
Corruption	Donate	Fundraising	Poverty
Donation	Equity	Squander	Savings
Gold Price	Expensive	Deficit	Luxury
Race	Prosperity	War in Afghanistan	Police Corruption
Reward	Expense	Aristocrat	Trustee in Bankruptcy
Abundance	Waste	Great Depression	Hole

Appendix C

This appendix provides the details of various correlation analysis which were completed, both on a country-specific level and as a form of robustness check.

Table C1: Correlation Analysis - Brazil

Correlation [Probability]	Bovespa Returns	Inflation	Industrial Production	Real Interest Rate	Risk Premium	Term Structure	Oil Price	FEARS
Bovespa Returns	1 [--]							
Inflation	-0.078662 [0.5334]	1 [--]						
Industrial Production	-0.146242 [0.2451]	0.075863 [0.5481]	1 [--]					
Real Interest Rate	-0.097511 [0.4397]	0.030682 [0.8083]	0.108126 [0.3913]	1 [--]				
Risk Premium	0.471548 [0.0001]*	-0.104104 [0.4092]	-0.017758 [0.8883]	-0.13664 [0.2778]	1 [--]			
Term Structure	-0.056144 [0.6569]	0.016408 [0.8968]	-0.084857 [0.5015]	-0.693282 [0.0000]*	-0.532123 [0.0000]*	1 [--]		
Oil Price	-0.031637 [0.8025]	0.097692 [0.4388]	0.086606 [0.4927]	-0.032344 [0.7981]	0.092386 [0.4642]	-0.057246 [0.6506]	1 [--]	
FEARS	-0.300384 [0.015]*	0.076555 [0.5444]	0.047907 [0.7047]	-0.002815 [0.9822]	-0.221963 [0.0756]**	0.062748 [0.6195]	-0.119164 [0.3444]	1 [--]

Note: p-values for coefficients provided in the square brackets below
*Statistically significant at the 5% level of significance
**Statistically significant at the 10% level of significance

Table C2: Correlation Analysis - Russia

Correlation [Probability]	Micex Returns	Inflation	Industrial Production	Real Interest Rate	Risk Premium	Term Structure	Oil Price	FEARS
Micex Returns	1 [--]							
Inflation	0.224285 [0.0725]**	1 [--]						
Industrial Production	-0.010449 [0.9342]	0.320771 [0.0092]*	1 [--]					
Real Interest Rate	0.16681 [0.1841]	0.007741 [0.9512]	-0.142873 [0.2562]	1 [--]				
Risk Premium	0.52813 [0.0000]*	0.086639 [0.4926]	0.004641 [0.9707]	-0.160209 [0.2024]	1 [--]			
Term Structure	-0.415892 [0.0006]*	-0.078363 [0.5349]	0.125912 [0.3176]	-0.839568 [0.0000]*	-0.385748 [0.0015]*	1 [--]		
Oil Price	0.044294 [0.7261]	0.242657 [0.0515]**	0.111088 [0.3783]	-0.092629 [0.463]	0.079307 [0.53]	0.018989 [0.8807]	1 [--]	
FEARS	0.373214 [0.0022]*	0.154604 [0.2188]	0.160392 [0.2018]	0.007094 [0.9553]	0.159131 [0.2055]	-0.04067 [0.7477]	0.098258 [0.4362]	1 [--]

Note: p-values for coefficients provided in the square brackets below

*Statistically significant at the 5% level of significance

**Statistically significant at the 10% level of significance

Table C3: Correlation Analysis - India

Correlation [Probability]	Nifty Returns	Inflation	Industrial Production	Real Interest Rate	Risk Premium	Term Structure	Oil Price	FEARS
Nifty Returns	1 [--]							
Inflation	-0.072292 [0.5671]	1 [--]						
Industrial Production	0.102154 [0.4181]	0.013409 [0.9156]	1 [--]					
Real Interest Rate	-0.170368 [0.1748]	-0.017708 [0.8887]	0.129727 [0.303]	1 [--]				
Risk Premium	0.488472 [0.0000]*	0.030647 [0.8085]	0.021767 [0.8634]	-0.179142 [0.1533]	1 [--]			
Term Structure	0.09022 [0.4748]	0.039592 [0.7542]	-0.188398 [0.1329]	-0.882288 [0.0000]*	-0.140873 [0.263]	1 [--]		
Oil Price	-0.047213 [0.7088]	0.013019 [0.918]	0.169862 [0.1761]	0.026062 [0.8367]	0.088013 [0.4857]	-0.065487 [0.6043]	1 [--]	
FEARS	-0.186127 [0.1377]	0.039133 [0.7569]	0.01792 [0.8873]	-0.098232 [0.4363]	-0.128542 [0.3075]	0.064566 [0.6094]	-0.077488 [0.5395]	1 [--]

Note: p-values for coefficients provided in the square brackets below
*Statistically significant at the 5% level of significance
**Statistically significant at the 10% level of significance

Table C4: Correlation Analysis - China

Correlation [Probability]	SSE Returns	Inflation	Industrial Production	Real Interest Rate	Risk Premium	Term Structure	Oil Price	FEARS
SSE Returns	1 [--]							
Inflation	-0.006205 [0.9689]	1 [--]						
Industrial Production	0.033894 [0.8313]	0.264905 [0.09]**	1 [--]					
Real Interest Rate	0.081037 [0.6099]	0.068846 [0.6649]	0.227854 [0.1467]	1 [--]				
Risk Premium	0.043292 [0.7854]	-0.119988 [0.4491]	-0.333239 [0.031]*	0.033854 [0.8315]	1 [--]			
Term Structure	-0.080345 [0.613]	-0.084461 [0.5949]	-0.087635 [0.581]	-0.92992 [0.0000]*	-0.367816 [0.0166]	1 [--]		
Oil Price	0.35239 [0.0221]*	-0.000835 [0.9958]	-0.228218 [0.146]	-0.3203 [0.0386]	0.051975 [0.7438]	0.258232 [0.0987]**	1 [--]	
FEARS	0.059789 [0.7068]	-0.255775 [0.1021]	-0.011692 [0.9414]	0.171937 [0.2763]	-0.03006 [0.8501]	-0.11096 [0.4842]	0.024949 [0.8754]	1 [--]

Note: p-values for coefficients provided in the square brackets below
*Statistically significant at the 5% level of significance
**Statistically significant at the 10% level of significance

Table C5: Correlation Analysis - South Africa

Correlation [Probability]	Alsi Returns	Inflation	Industrial Production	Real Interest Rate	Risk Premium	Term Structure	Oil Price	FEARS
Alsi Returns	1 [--]							
Inflation	0.050144 [0.6916]	1 [--]						
Industrial Production	-0.12802 [0.3095]	0.390172 [0.0013]*	1 [--]					
Real Interest Rate	-0.095286 [0.4502]	0.023909 [0.8501]	0.23038 [0.0649]**	1 [--]				
Risk Premium	0.35164 [0.0041]*	0.16584 [0.1867]	-0.146696 [0.2436]	-0.111155 [0.378]	1 [--]			
Term Structure	-0.08981 [0.4768]	-0.135176 [0.283]	0.010562 [0.9335]	-0.491483 [0.0000]*	-0.747947 [0.0000]*	1 [--]		
Oil Price	-0.023359 [0.8535]	-0.169656 [0.1767]	-0.164642 [0.19]	-0.20912 [0.0946]**	0.061276 [0.6278]	0.066436 [0.599]	1 [--]	
FEARS	-0.490638 [0.0000]*	0.036625 [0.7721]	0.094453 [0.4542]	0.033293 [0.7923]	-0.041504 [0.7427]	-0.051966 [0.681]	-0.013633 [0.9142]	1 [--]

Note: p-values for coefficients provided in the square brackets below
*Statistically significant at the 5% level of significance
**Statistically significant at the 10% level of significance

Table C6: Correlation Analysis - Germany

Correlation [Probability]	DAX Returns	Inflation	Industrial Production	Real Interest Rate	Risk Premium	Term Structure	Oil Price	FEARS
DAX Returns	1 [--]							
Inflation	0.055053 [0.6632]	1 [--]						
Industrial Production	0.218466 [0.0804]**	0.182831 [0.1449]	1 [--]					
Real Interest Rate	0.014977 [0.9057]	-0.071953 [0.569]	0.099128 [0.4321]	1 [--]				
Risk Premium	0.082396 [0.5141]	-0.078784 [0.5327]	-0.207978 [0.0964]**	0.048185 [0.7031]	1 [--]			
Term Structure	-0.015784 [0.9007]	0.083686 [0.5075]	-0.050439 [0.6899]	-0.979559 [0.0000]*	-0.246931 [0.0474]*	1 [--]		
Oil Price	0.079948 [0.5267]	-0.18042 [0.1504]	-0.160352 [0.202]	0.103586 [0.4116]	0.064564 [0.6094]	-0.115054 [0.3614]	1 [--]	
FEARS	-0.386245 [0.0015]*	-0.019408 [0.878]	-0.250194 [0.0444]*	0.263501 [0.0339]*	0.228764 [0.0668]**	-0.30979 [0.012]*	-0.043405 [0.7314]	1 [--]

Note: p-values for coefficients provided in the square brackets below
*Statistically significant at the 5% level of significance
**Statistically significant at the 10% level of significance

Table C7: Correlation Analysis - Japan

Correlation [Probability]	Nikkei Returns	Inflation	Industrial Production	Real Interest Rate	Risk Premium	Term Structure	Oil Price	FEARS
Nikkei Returns	1 [--]							
Inflation	-0.03285 [0.8364]	1 [--]						
Industrial Production	0.019121 [0.9043]	-0.134217 [0.3968]	1 [--]					
Real Interest Rate	-0.203789 [0.1955]	0.09075 [0.5676]	0.235097 [0.1339]	1 [--]				
Risk Premium	-0.25021 [0.11]	-0.062128 [0.6959]	0.022329 [0.8884]	-0.090014 [0.5708]	1 [--]			
Term Structure	0.267368 [0.0869]**	-0.083014 [0.6012]	-0.254228 [0.1042]	-0.967318 [0.0000]*	-0.162164 [0.3049]	1 [--]		
Oil Price	0.006437 [0.9677]	-0.266391 [0.0881]**	0.008591 [0.9569]	-0.029983 [0.8505]	-0.050549 [0.7506]	0.043803 [0.783]	1 [--]	
FEARS	0.47118 [0.0016]*	0.132403 [0.4032]	-0.021014 [0.8949]	-0.348651 [0.0236]*	-0.068878 [0.6647]	0.365015 [0.0175]*	-0.245211 [0.1175]	1 [--]

Note: p-values for coefficients provided in the square brackets below
*Statistically significant at the 5% level of significance
**Statistically significant at the 10% level of significance

Table C8: Correlation Analysis - United Kingdom

Correlation [Probability]	FTSE 100 Returns	Inflation	Industrial Production	Real Interest Rate	Risk Premium	Term Structure	Oil Price	FEARS
FTSE 100 Returns	1 [--]							
Inflation	0.0145 [0.9095]	1 [--]						
Industrial Production	0.209646 [0.0964]**	0.507589 [0.0000]*	1 [--]					
Real Interest Rate	-0.043445 [0.7332]	-0.965227 [0.0000]*	-0.476441 [0.0001]*	1 [--]				
Risk Premium	-0.212208 [0.0923]**	-0.135892 [0.2843]	-0.288757 [0.0207]*	0.19052 [0.1316]	1 [--]			
Term Structure	0.198921 [0.1151]	0.136625 [0.2817]	0.307177 [0.0135]*	-0.204444 [0.1051]	-0.969057 [0.0000]*	1 [--]		
Oil Price	-0.028111 [0.8255]	-0.307856 [0.0133]	-0.329867 [0.0078]*	0.348932 [0.0047]*	0.021027 [0.869]	-0.039742 [0.7552]	1 [--]	
FEARS	-0.557048 [0.0000]*	0.040948 [0.748]	0.020829 [0.8702]	-0.029779 [0.8153]	0.120371 [0.3434]	-0.115951 [0.3616]	-0.062562 [0.6233]	1 [--]

Note: p-values for coefficients provided in the square brackets below
*Statistically significant at the 5% level of significance
**Statistically significant at the 10% level of significance

Table C9: Correlation Analysis - United States

Correlation [Probability]	S&P500 Returns	Inflation	Industrial Production	Real Interest Rate	Risk Premium	Term Structure	Oil Price	FEARS
S&P500 Returns	1							
	[--]							
Inflation	0.058061	1						
	[0.6459]	[--]						
Industrial Production	-0.099243	-0.103066	1					
	[0.4316]	[0.4139]	[--]					
Real Interest Rate	0.054826	-0.091445	-0.04042	1				
	[0.6645]	[0.4688]	[0.7492]	[--]				
Risk Premium	-0.531978	-0.173833	0.142753	0.09705	1			
	[0.0000]*	[0.1661]	[0.2566]	[0.4418]	[--]			
Term Structure	0.175322	0.160391	-0.021203	-0.906707	-0.502887	1		
	[0.1624]	[0.2018]	[0.8669]	[0.0000]*	[0.0000]*	[--]		
Oil Price	-0.06795	-0.212884	-0.162325	0.194104	-0.003214	-0.172891	1	
	[0.5907]	[0.0886]**	[0.1964]	[0.1213]	[0.9797]	[0.1684]	[--]	
FEARS	-0.391776	0.042429	0.061072	-0.16305	0.123116	0.08263	-0.078972	1
	[0.0012]*	[0.7372]	[0.6289]	[0.1944]	[0.3285]	[0.5129]	[0.5318]	[--]

Note: p-values for coefficients provided in the square brackets below
*Statistically significant at the 5% level of significance
**Statistically significant at the 10% level of significance

Table C10: Correlation Analysis - VIX and FEARS

(1) India

Correlation [Probability]	Nifty VIX	FEARS
Nifty VIX	1 [--]	
FEARS	0.051435 [0.6841]	1 [--]

(2) South Africa

Correlation [Probability]	SAVI	FEARS
SAVI	1 [--]	
FEARS	0.23683 [0.0575]**	1 [--]

(3) Germany

Correlation [Probability]	VDAX	FEARS
VDAX	1 [--]	
FEARS	0.335216 [0.0063]*	1 [--]

(4) Japan

Correlation [Probability]	Nikkei VIX	FEARS
Nikkei VIX	1 [--]	
FEARS	-0.212668 [0.1763]	1 [--]

(5) United Kingdom

Correlation [Probability]	FTSE VIX	FEARS
FTSE VIX	1 [--]	
FEARS	0.334866 [0.0068]*	1 [--]

(6) United States

Correlation [Probability]	S&P500 VIX	FEARS
S&P500 VIX	1 [--]	
FEARS	0.361418 [0.0031]*	1 [--]

Note: p-values for coefficients provided in the square brackets below
*Statistically significant at the 5% level of significance
**Statistically significant at the 10% level of significance

Appendix D

This appendix provides details of the robustness checks performed for each country, specific to the regression model which was deemed to be superior based on the Adjusted-R^2.

Endogeneity is tested through a correlation analysis between the residual of the specific model and each individual variable. The error term is tested for both stationarity and normality. Finally, the regression model is tested for ARCH effects or serial correlation.

Leverage plots provide a graphical indication of how well the explanatory variables explain the model – the closer the blue dots are to the red fit line the better the model in terms of fit. Influence statistics provides an indication of the outliers in the overall model as well as per explanatory variable.

The results from the robustness checks on each country are provided in Table D1 below.

Table D1: Robustness Checks

	Brazil	**Russia**	**India**	**China**	**South Africa**	**Germany**	**Japan**	**UK**	**US**
Model No.	**(1)**	**(2)**	**(1)**	**(1)**	**(2)**	**(2)**	**(2)**	**(2)**	**(2)**
Stationarity – ADF Test	-6.713164 [0.0000]*	-7.006464 [0.0000]*	7.213064 [0.0000]*	-6.125111 [0.0000]*	-5.89381 [0.0000]*	-9.268394 [0.0000]*	-5.058719 [0.0010]*	-8.509349 [0.0000]*	-7.778723 [0.0000]*
Normality – JB Test	0.410599 [0.814403]	0.097921 [0.952219]	0.865233 [0.648809]	0.54434 [0.761725]	0.170339 [0.918357]	9.741223 [0.007669]*	4.957676 [0.083841]**	4.423193 [0.109526]	1.043247 [0.593556]
ARCH Effects - Lagrange Multiplier	2.717244 [0.0993]**	2.088637 [0.1484]	0.182285 [0.6694]	1.022831 [0.3118]	1.211815 [0.2710]	0.117477 [0.7318]	0.665767 [0.4145]	0.143616 [0.7047]	0.194468 [0.6592]
ARCH Effects - Lagrange Multiplier	0.656078 [0.4179]	1.034204 [0.3092]	0.323208 [0.5697]	0.00849 [0.9266]	0.762349 [0.3826]	1.58605 [0.2079]	1.960747 [0.1614]	1.542787 [0.2142]	0.036847 [0.8478]

Note: p-values for coefficients provided in the square brackets below the coefficient

*Statistically significant at the 5% level of significance; **Statistically significant at the 10% level of significance

1. Brazil

Endogeneity tests were conducted on regression models (1) and (2) and all variables were found to be exogenous. The robustness checks on (1) can also be found in Table D1 above. The residual of (1) was found to be stationary and normally distributed. ARCH effects were found to be present under the LM test which can occur if the disturbance terms are serially correlated. Using the more robust Breusch-Godfrey test revealed that there were no ARCH effects present. The leverage plots and influence statistics (Figure D1 and Table D2 below) indicate the presence of outliers. Overall, (1) possibly lacks some explanatory power due to redundant variables, serially correlated residuals and the presence of outliers.

Leverage plots and influence statistics were completed for model (1) – a macroeconomic APT model without the FEARS variable.

Figure D1: Leverage Plots - Brazil

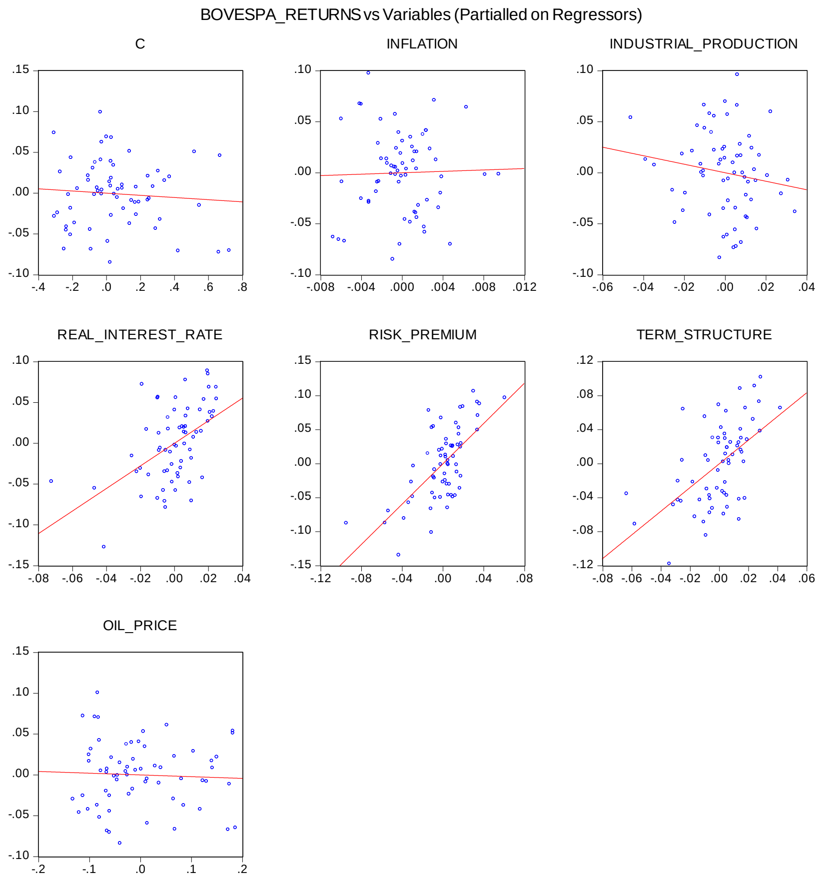

Table D2: Influence Statistics - Brazil

Obs.	Resid.	RStudent	DFFITS	COVRATIO	Hat Matrix
2010M02	0.024999	0.622964	-0.196004	1.183692	0.090076
2010M03	0.020000	0.501989	-0.172139	1.223896	0.105218
2010M04	-0.039674	-0.977748	0.248063	1.070039	0.060475
2010M05	-0.007637	-0.206104	0.112272	1.457000	0.228834
2010M06	-0.060710	-1.603425	0.697593	0.986365	0.159156
2010M07	0.054845	1.462140	-0.686783	1.065420	0.180750
2010M08	-0.063442	-1.687664	0.756510	0.964179	0.167316
2010M09	0.057555	1.471033	-0.512563	0.975799	0.108264
2010M10	0.011583	0.286347	-0.084675	1.215930	0.080412
2010M11	-0.005326	-0.134147	0.048409	1.273729	0.115220
2010M12	0.031033	0.765599	-0.207490	1.128631	0.068424
2011M01	-0.035566	-0.872269	0.209485	1.088715	0.054532
2011M02	0.024021	0.585931	-0.135945	1.141268	0.051082
2011M03	0.011365	0.272754	-0.043049	1.147078	0.024305
2011M04	-0.058958	-1.476805	0.409244	0.935092	0.071316
2011M05	-0.009171	-0.225782	0.063506	1.211216	0.073314
2011M06	-0.028061	-0.690500	0.182646	1.140036	0.065391
2011M07	-0.065148	-1.659160	0.531134	0.895071	0.092953
2011M08	0.009680	0.257629	-0.131513	1.412231	0.206716
2011M09	0.053197	1.624633	-1.246168	1.306803	0.370419
2011M10	0.007160	0.186896	-0.086339	1.364636	0.175875
2011M11	0.018946	0.462154	-0.109659	1.162223	0.053300
2011M12	0.005605	0.140984	-0.050263	1.269920	0.112771
2012M01	0.034679	0.924255	-0.459342	1.269153	0.198072
2012M02	-0.000624	-0.015280	0.003974	1.205844	0.063369
2012M03	-0.026839	-0.654488	0.148849	1.127231	0.049180
2012M04	-0.038939	-0.963856	0.262663	1.083512	0.069130
2012M05	-0.070078	-1.828419	0.698201	0.868395	0.127261
2012M06	-0.017740	-0.437963	0.125674	1.194052	0.076077
2012M07	-0.001585	-0.039099	0.011312	1.223769	0.077235
2012M08	0.005959	0.145995	-0.038436	1.204590	0.064818
2012M09	0.019957	0.483247	-0.097299	1.142091	0.038960
2012M10	-0.053898	-1.344201	0.366284	0.975226	0.069120
2012M11	-0.002580	-0.062899	0.015287	1.195595	0.055772
2012M12	0.040589	0.998041	-0.242097	1.059342	0.055571
2013M01	-0.021235	-0.524443	0.149801	1.181137	0.075434
2013M02	-0.045881	-1.130615	0.273000	1.023431	0.055092
2013M03	0.009003	0.224816	-0.074596	1.246060	0.099179
2013M04	0.003560	0.087047	-0.022192	1.201752	0.061027
2013M05	-0.008359	-0.209966	0.073764	1.262014	0.109862
2013M06	-0.024084	-0.654899	0.363258	1.401460	0.235280
2013M07	-0.006959	-0.189365	0.106860	1.482589	0.241529
2013M08	0.068533	1.805726	-0.744694	0.895313	0.145357
2013M09	0.029587	0.756413	-0.295936	1.214401	0.132746
2013M10	0.003382	0.082407	-0.019785	1.193574	0.054503
2013M11	0.001888	0.048126	-0.019101	1.307013	0.136090
2013M12	-0.027864	-0.698339	0.231350	1.180858	0.098896
2014M01	-0.048691	-1.207325	0.315336	1.011037	0.063861
2014M02	-0.032481	-0.846121	0.372819	1.235903	0.162582
2014M03	0.069853	1.770597	-0.516642	0.842540	0.078461
2014M04	0.022458	0.550008	-0.138180	1.157076	0.059371
2014M05	-0.044423	-1.096757	0.276775	1.038000	0.059871
2014M06	0.014433	0.356234	-0.102728	1.204490	0.076774
2014M07	0.069065	1.761863	-0.556332	0.856921	0.090666
2014M08	0.098759	2.600494	-0.840403	0.569085	0.094563
2014M09	-0.084536	-2.218031	0.797255	0.714441	0.114417
2014M10	0.014108	0.345649	-0.089740	1.188055	0.063150

2014M11	0.039470	0.970089	-0.235416	1.066453	0.055616
2014M12	-0.003254	-0.088050	0.048591	1.472031	0.233448
2015M01	-0.004535	-0.123672	0.070488	1.493563	0.245198
2015M02	0.062045	1.605968	-0.605417	0.946337	0.124430
2015M03	-0.004634	-0.121069	0.056234	1.370664	0.177456
2015M04	0.040461	1.004983	-0.284507	1.078842	0.074197
2015M05	-0.071686	-1.820931	0.535630	0.826073	0.079635
2015M06	0.036817	0.896735	-0.184522	1.067318	0.040622

Note: Outliers are highlighted in red

Obs.	C	INFLATION	INDUSTRIAL_ PRODUCTION	REAL_INTE REST_RATE	RISK_PREMI UM	TERM_STR UCTURE	OIL_PRICE
2010M02	0.090076	0.121180	0.025733	-0.001719	-0.043376	-0.012141	-0.001961
2010M03	0.105218	0.090729	0.030067	0.033508	0.095620	0.094716	0.080319
2010M04	0.060475	-0.145890	-0.052929	-0.089152	-0.014474	-0.033803	-0.023083
2010M05	0.228834	-0.064024	0.021168	0.020273	0.004137	0.041111	0.040247
2010M06	0.159156	-0.631794	0.465374	-0.013174	-0.114105	-0.150617	-0.155058
2010M07	0.180750	0.539850	-0.378535	-0.099423	0.010086	0.165040	0.051114
2010M08	0.167316	-0.610940	0.451990	0.010629	0.075698	-0.093755	-0.037003
2010M09	0.108264	0.403085	-0.041476	0.015044	0.223890	0.139229	0.246903
2010M10	0.080412	0.040906	0.039046	-0.005237	0.012411	0.015286	0.010431
2010M11	0.115220	-0.017330	-0.021716	-0.001814	-0.001216	0.006953	-0.006118
2010M12	0.068424	0.120903	0.001087	0.047314	0.046252	0.013488	-0.003188
2011M01	0.054532	-0.061395	-0.126052	0.005521	-0.024560	-0.017810	-0.012545
2011M02	0.051082	0.073473	-0.013626	0.082379	0.029338	0.010691	0.015794
2011M03	0.024305	0.012872	0.011716	0.008668	0.013321	0.013347	0.009644
2011M04	0.071316	-0.005424	-0.133388	0.307491	-0.008248	-0.066303	-0.055169
2011M05	0.073314	-0.019820	0.002841	-0.052606	-0.010200	-0.006364	-0.010196
2011M06	0.065391	-0.112901	0.091535	0.113717	0.020689	0.038009	0.031385
2011M07	0.092953	-0.367813	0.387420	-0.111329	-0.208240	-0.110458	-0.199896
2011M08	0.206716	0.025162	-0.016665	-0.049606	-0.098472	-0.080541	-0.109558
2011M09	0.370419	0.138763	-0.168798	-0.088543	-1.073217	-1.011778	-0.851725
2011M10	0.175875	0.009608	-0.008451	-0.004947	0.034484	0.064973	0.056294
2011M11	0.053300	0.006694	-0.002542	0.023326	-0.085895	-0.076432	-0.088093
2011M12	0.112771	0.005096	-0.003730	0.037616	-0.008983	0.002167	0.004138
2012M01	0.198072	0.021777	0.033652	-0.389171	0.183901	0.193256	0.184969
2012M02	0.063369	-0.000358	0.000674	-0.001242	-0.002265	-0.002787	-0.002888
2012M03	0.049180	-0.009447	0.086052	-0.007989	0.028185	0.000144	0.006719
2012M04	0.069130	0.093723	-0.048098	-0.082755	0.140565	0.040795	0.109830
2012M05	0.127261	0.089387	0.017304	-0.085292	0.587091	0.442676	0.438625
2012M06	0.076077	-0.022823	0.045552	-0.038194	0.049884	-0.004452	0.025621
2012M07	0.077235	0.000594	0.001039	-0.005010	0.001501	-0.003670	-0.000698
2012M08	0.064818	-0.004191	-0.004656	0.025425	0.006268	0.011501	0.013243
2012M09	0.038960	-0.026360	0.023784	-0.021470	0.054116	0.040224	0.047423
2012M10	0.069120	0.147635	-0.118576	-0.056006	0.099645	-0.038340	0.096963
2012M11	0.055772	0.002288	-0.000910	0.005587	-0.000113	-0.001654	-0.003934
2012M12	0.055571	-0.107320	0.094549	0.099315	0.001218	0.069773	0.008551
2013M01	0.075434	0.057580	-0.081061	-0.057247	-0.037098	-0.037881	-0.060032
2013M02	0.055092	0.056130	-0.012274	0.194647	0.011057	0.015419	0.036503
2013M03	0.099179	0.002916	0.000525	0.027653	0.035816	0.003146	0.023303
2013M04	0.061027	-0.001202	0.001490	0.006256	-0.005801	-0.003886	-0.010633
2013M05	0.109862	-0.021217	0.021401	0.001243	-0.018276	0.009956	-0.022636
2013M06	0.235280	-0.065637	0.117887	-0.209167	0.008010	0.148816	0.065354
2013M07	0.241529	-0.016040	0.050572	0.061473	-0.024817	-0.005243	0.001127
2013M08	0.145357	0.027877	-0.307932	0.094650	0.092564	-0.094757	0.181505
2013M09	0.132746	-0.032240	-0.075031	0.086317	0.102058	0.066485	0.020482
2013M10	0.054503	-0.007241	0.004673	-0.008225	0.004149	0.007862	0.006930
2013M11	0.136090	-0.001280	-0.000852	0.001964	0.008347	-0.000596	0.006433

2013M12	0.098896	0.105854	-0.071058	0.154453	-0.021966	-0.008102	-0.019543
2014M01	0.063861	0.147793	-0.038941	-0.158027	0.058938	0.077085	0.052989
2014M02	0.162582	0.141740	-0.058130	-0.038956	-0.067700	-0.065513	0.038669
2014M03	0.078461	-0.284460	0.227318	0.001511	-0.128770	-0.016774	-0.004954
2014M04	0.059371	-0.077151	0.061147	-0.005385	-0.014877	-0.002004	-0.034780
2014M05	0.059871	0.133107	-0.063762	0.069501	-0.019337	-0.102929	-0.037526
2014M06	0.076774	-0.019802	-0.029648	-0.048764	0.008633	0.015455	0.018640
2014M07	0.090666	-3.23E-05	-0.302255	0.335897	-0.132080	-0.104454	-0.119006
2014M08	0.094563	-0.048654	-0.352323	0.133492	-0.378773	-0.197081	-0.444531
2014M09	0.114417	-0.026653	0.086205	0.051660	-0.172758	0.138260	-0.209914
2014M10	0.063150	0.003287	-0.021353	-0.000450	0.011747	-0.003603	-0.017431
2014M11	0.055616	0.013066	-0.013365	-0.081509	-0.118495	-0.150174	-0.166294
2014M12	0.233448	-0.012605	0.000354	0.031934	0.014519	0.029733	0.018678
2015M01	0.245198	-0.004520	-0.045519	-0.013141	0.022799	0.022064	0.029385
2015M02	0.124430	-0.024424	0.425171	-0.143890	0.240890	0.267643	0.319686
2015M03	0.177456	0.014927	-0.049707	0.012638	-0.012668	-0.007175	-0.012895
2015M04	0.074197	-0.016893	0.097004	-0.115537	0.154949	0.183729	0.122651
2015M05	0.079635	0.236468	-0.352501	-0.064870	0.071041	-0.044943	0.113207
2015M06	0.040622	-0.030529	0.073237	-0.050459	-0.025225	-0.070371	-0.027493

Note: Outliers are highlighted in red

The influence statistics indicate the presence of outliers.

1. RStudent: 2 outliers
2. DFFITS: 8 outliers
3. COVRATIO: 9 outliers
4. Hat Matrix: 29 outliers
5. DFBETAS
    - Intercept: 1 outliers
    - Inflation: 6 outliers
    - Industrial Production: 9 outliers
    - Real Interest Rate: 3 outliers
    - Risk Premium: 3 outliers
    - Term Structure: 3 outliers
    - Oil Price: 4 outliers

The results from the leverage plots and influence statistics indicate that model (1) possibly lacks some explanatory power due to redundant variables, serially correlated residuals and the presence of outliers.

2. Russia

Endogeneity tests were conducted on both regression models (1) and (2) and all variables were found to be exogenous. The robustness checks on (2) can also be found in Table D1 above. The residual of (2) was found to be stationary, normally distributed and no ARCH effects were found to be present. The leverage plots and influence statistics (Figure D2 and Table D3 below) indicate that outliers are not an issue in this model. Overall, (2) suffers from redundant variables, serially correlated residuals but not necessarily from the presence of outliers.

Leverage plots and influence statistics were completed for model (2) – a macroeconomic APT model with the FEARS variable included.

Figure D2: Leverage Plots - Russia

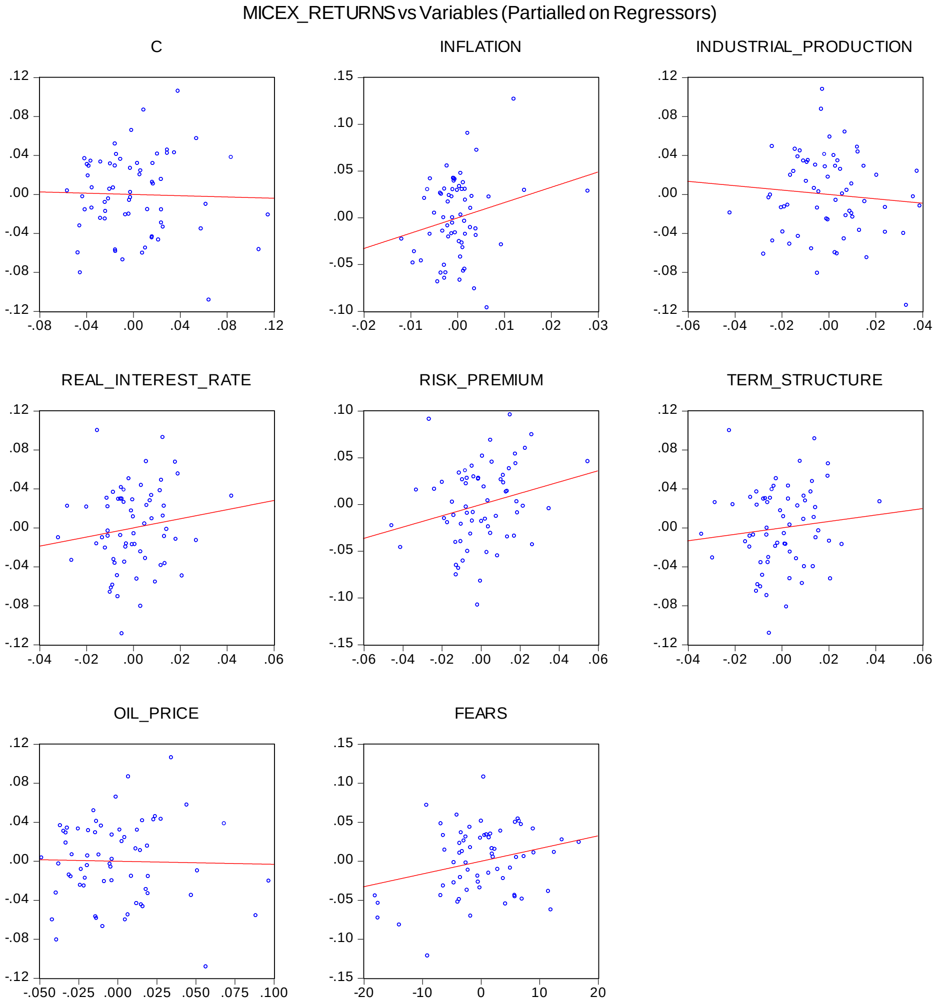

Table D3: Influence Statistics - Russia

Obs.	Resid.	RStudent	DFFITS	COVRATIO	Hat Matrix
2010M02	-0.044194	-1.093314	0.459740	1.145050	0.150253
2010M03	0.026735	0.637808	-0.211208	1.206526	0.098822
2010M04	0.024297	0.576683	-0.182137	1.208419	0.090704
2010M05	-0.033510	-0.814660	0.312463	1.202726	0.128245
2010M06	-0.028600	-0.713315	0.327413	1.297476	0.174020
2010M07	0.059039	1.417138	-0.430637	0.949375	0.084536
2010M08	-0.008188	-0.196672	0.071488	1.297150	0.116706
2010M09	0.043701	1.043682	-0.328014	1.085104	0.089896
2010M10	0.046392	1.095897	-0.295894	1.043110	0.067948
2010M11	0.032169	0.776153	-0.280951	1.196170	0.115849
2010M12	0.040438	0.943070	-0.213831	1.067877	0.048897
2011M01	0.065544	1.571385	-0.447586	0.881976	0.075043
2011M02	0.006005	0.148535	-0.066612	1.379463	0.167439
2011M03	-0.015218	-0.363392	0.124392	1.263085	0.104885
2011M04	0.001764	0.044659	-0.022713	1.449710	0.205508
2011M05	-0.060120	-1.434255	0.400830	0.930716	0.072445
2011M06	-0.043021	-1.089340	0.525876	1.201213	0.189000
2011M07	-0.009165	-0.220413	0.080953	1.298486	0.118861
2011M08	-0.032857	-0.803524	0.322501	1.220483	0.138739
2011M09	-0.021191	-0.555280	0.324295	1.478672	0.254332
2011M10	0.012968	0.350722	-0.230891	1.622700	0.302357
2011M11	0.035244	0.864319	-0.351667	1.207763	0.142032
2011M12	-0.059128	-1.440166	0.506034	0.967606	0.109894
2012M01	0.032835	0.777742	-0.233369	1.152414	0.082599
2012M02	0.029477	0.692681	-0.190015	1.157079	0.069984
2012M03	-0.061475	-1.467888	0.410558	0.918399	0.072552
2012M04	-0.026113	-0.599208	0.099415	1.124818	0.026789
2012M05	-0.067498	-1.649269	0.566988	0.881493	0.105694
2012M06	0.041946	0.975959	-0.207845	1.052350	0.043386
2012M07	-0.018243	-0.426755	0.113841	1.202454	0.066433
2012M08	0.005615	0.136068	-0.053219	1.324849	0.132679
2012M09	-0.003336	-0.085648	0.046444	1.489335	0.227235
2012M10	-0.015027	-0.369809	0.159691	1.340530	0.157163
2012M11	-0.054849	-1.301166	0.351025	0.973918	0.067842
2012M12	0.043214	1.015309	-0.257830	1.059888	0.060580
2013M01	0.031861	0.734338	-0.133979	1.102604	0.032215
2013M02	-0.057528	-1.363854	0.356519	0.947703	0.063962
2013M03	-0.015126	-0.347439	0.063974	1.170830	0.032793
2013M04	-0.046041	-1.088909	0.299694	1.048114	0.070414
2013M05	0.016115	0.381909	-0.120823	1.241323	0.090982
2013M06	0.004731	0.115259	-0.046901	1.340335	0.142060
2013M07	0.032270	0.748770	-0.162040	1.113681	0.044738
2013M08	-0.003965	-0.093382	0.027864	1.253126	0.081754
2013M09	0.051220	1.203760	-0.288299	0.993023	0.054248
2013M10	0.020214	0.468484	-0.105576	1.173325	0.048331
2013M11	-0.006216	-0.146880	0.045541	1.258985	0.087704
2013M12	-0.005307	-0.122068	0.023986	1.194052	0.037175
2014M01	0.028725	0.683930	-0.220675	1.190161	0.094291
2014M02	-0.025535	-0.648503	0.328892	1.364291	0.204586
2014M03	-0.033924	-0.797984	0.217664	1.130778	0.069250
2014M04	-0.081970	-2.047955	0.767500	0.737296	0.123152
2014M05	0.027862	0.662411	-0.210961	1.192155	0.092086
2014M06	0.017646	0.408150	-0.089026	1.178584	0.045416
2014M07	-0.020307	-0.484471	0.162918	1.240198	0.101595
2014M08	0.001817	0.041875	-0.008737	1.201964	0.041716
2014M09	0.030679	0.730702	-0.235105	1.178440	0.093812
2014M10	0.086729	2.093321	-0.517290	0.669085	0.057551

2014M11	0.035625	0.839936	-0.234694	1.123691	0.072421
2014M12	0.011259	0.307066	-0.207848	1.657518	0.314210
2015M01	0.107187	3.504565	-2.977385	0.406001	0.419204
2015M02	-0.017047	-0.517854	0.464273	2.000219	0.445606
2015M03	-0.106521	-3.051857	1.886623	0.465066	0.276493
2015M04	-0.017504	-0.461332	0.276407	1.518899	0.264155
2015M05	-0.053250	-1.376538	0.714468	1.120664	0.212223
2015M06	0.040651	0.990045	-0.376780	1.148020	0.126510

Note: Outliers are highlighted in red

Obs.	C	INFLATION	INDUSTRIAL_ PRODUCTION	REAL_INTE REST_RATE	RISK_PREMI UM	TERM_STR UCTURE	OIL_PRICE	FEARS
2010M02	0.150253	-0.065089	-0.242036	-0.057112	-0.134680	-0.147970	-0.143910	-0.073215
2010M03	0.098822	-0.005859	-0.026140	0.024852	-0.070506	-0.036971	-0.064785	-0.009841
2010M04	0.090704	0.012805	-0.015847	0.091478	0.041807	0.050138	0.055382	0.011187
2010M05	0.128245	-0.173501	0.146931	-0.155213	0.031556	0.065475	0.047264	-0.167450
2010M06	0.174020	-0.064593	-0.015948	0.244698	0.062880	0.029951	0.039928	-0.058021
2010M07	0.084536	0.274698	-0.072714	0.005390	0.255924	0.280262	0.266930	0.267326
2010M08	0.116706	-0.044583	0.026716	-0.037300	-0.028634	-0.027923	-0.029857	-0.043454
2010M09	0.089896	0.131833	-0.021469	-0.194907	-0.053668	-0.035889	-0.033407	0.123411
2010M10	0.067948	0.113172	0.016670	0.104205	0.209037	0.187757	0.202841	0.111290
2010M11	0.115849	0.047348	-0.126809	0.230113	-0.043376	-0.056603	-0.058439	0.042419
2010M12	0.048897	-0.047783	-0.015103	0.015966	-0.079455	-0.078661	-0.094298	-0.053111
2011M01	0.075043	-0.008175	0.145248	0.083655	0.086358	0.058543	0.116394	-0.007481
2011M02	0.167439	-0.009571	0.050757	0.009252	0.020037	0.015837	0.020383	-0.008002
2011M03	0.104885	0.046799	0.004357	-0.025400	0.044200	0.028221	0.047933	0.048507
2011M04	0.205508	-0.009690	0.000760	0.002175	-0.005226	-0.002764	-0.002885	-0.009915
2011M05	0.072445	-0.040082	0.089734	-0.039520	-0.134929	-0.091051	-0.118078	-0.029376
2011M06	0.189000	-0.067149	-0.016365	0.175655	-0.157662	-0.119088	-0.105603	-0.059856
2011M07	0.118861	0.019415	0.016366	0.044306	0.035326	0.029196	0.033184	0.022266
2011M08	0.138739	-0.075775	0.179695	-0.204359	0.065095	0.081593	0.070418	-0.068530
2011M09	0.254332	0.014884	0.129292	-0.048340	0.162751	0.192623	0.172997	0.022315
2011M10	0.302357	0.023462	-0.045209	0.030549	0.169848	0.167037	0.159874	0.019812
2011M11	0.142032	-0.132931	-0.056128	0.026272	-0.251789	-0.224638	-0.241836	-0.139695
2011M12	0.109894	0.079340	-0.042152	-0.030415	-0.306756	-0.292708	-0.287735	0.084052
2012M01	0.082599	-0.101175	0.006930	-0.052625	0.089275	0.105228	0.091676	-0.106786
2012M02	0.069984	-0.096808	-0.000839	0.015425	0.053562	0.075663	0.062029	-0.100853
2012M03	0.072552	0.247604	0.141383	-0.183311	0.144964	0.126643	0.150750	0.259972
2012M04	0.026789	0.050166	-0.004833	0.001687	-0.018445	-0.016594	-0.019695	0.053230
2012M05	0.105694	0.054166	-0.018929	0.358223	0.111215	0.161659	0.101057	0.067669
2012M06	0.043386	0.070326	-0.012294	-0.089756	0.033148	0.041255	0.024915	0.064463
2012M07	0.066433	0.035709	-0.037605	0.066082	0.013907	-0.000912	0.010841	0.037444
2012M08	0.132679	-0.017606	0.008960	0.038924	0.011118	0.013757	0.012403	-0.017324
2012M09	0.227235	0.000759	0.025414	-0.027980	0.010134	0.009870	0.010726	0.001933
2012M10	0.157163	-0.033212	-0.024024	0.051941	-0.051603	-0.063155	-0.053244	-0.032178
2012M11	0.067842	-0.048255	0.073771	0.165952	0.113511	0.090492	0.125791	-0.036204
2012M12	0.060580	0.104786	-0.017485	-0.110807	0.120753	0.133629	0.124143	0.098372
2013M01	0.032215	0.009062	-0.016537	-0.059431	-0.034710	-0.020255	-0.033330	0.004042
2013M02	0.063962	0.073948	-0.046270	0.076608	0.127398	0.129951	0.115918	0.080925
2013M03	0.032793	-0.014680	0.009580	0.012801	0.010060	0.011268	0.005794	-0.012516
2013M04	0.070414	-0.083406	0.069964	0.108574	0.074505	0.056027	0.084544	-0.074471
2013M05	0.090982	0.032756	0.014543	-0.048300	0.050667	0.033862	0.052260	0.030991
2013M06	0.142060	-0.008657	-0.007968	-0.005686	-0.038223	-0.041352	-0.038771	-0.009771
2013M07	0.044738	-0.073312	-0.061074	0.084869	-0.046554	-0.039904	-0.048948	-0.078649
2013M08	0.081754	0.014468	0.002287	-0.011042	0.012357	0.013237	0.012088	0.014974
2013M09	0.054248	-0.066001	-0.157756	0.111473	-0.021972	0.006672	-0.027699	-0.077313
2013M10	0.048331	0.009378	-0.020985	-0.053044	0.026805	0.035895	0.029510	0.005390
2013M11	0.087704	0.001714	-0.005019	0.028339	-0.000353	0.004428	-0.001359	0.002774

2013M12	0.037175	0.009008	0.005675	-0.002838	0.006507	0.006345	0.007343	0.009889
2014M01	0.094291	-0.038363	0.015121	-0.030096	-0.002263	-0.006489	0.018230	-0.041706
2014M02	0.204586	0.070002	-0.062907	0.005018	-0.188482	-0.184395	-0.169712	0.070882
2014M03	0.069250	0.129933	-0.020165	-0.080053	-0.041569	-0.029334	-0.046451	0.132682
2014M04	0.123152	0.339711	-0.172906	0.078375	-0.064930	0.004344	-0.039941	0.348053
2014M05	0.092086	-0.090705	0.024966	-0.007721	-0.026604	-0.006963	-0.038678	-0.093648
2014M06	0.045416	-0.055222	0.028011	-0.000900	-0.003515	0.004775	-0.002208	-0.056281
2014M07	0.101595	0.006656	-0.018637	-0.027712	-0.089731	-0.069454	-0.094216	0.007815
2014M08	0.041716	-0.000351	-0.001015	-0.001350	0.001978	0.001080	0.001321	-0.000627
2014M09	0.093812	-0.051542	-0.057911	-0.052144	-0.146810	-0.133128	-0.145667	-0.058538
2014M10	0.057551	0.065417	0.102490	-0.050107	0.260979	0.234425	0.275992	0.060494
2014M11	0.072421	-0.032646	0.023019	-0.085066	-0.094593	-0.125474	-0.105400	-0.037488
2014M12	0.314210	0.021578	0.054061	-0.026439	-1.41E-05	-0.039586	0.002489	0.021987
2015M01	0.419204	0.604177	1.205370	-0.092288	-0.678916	-0.886510	-0.937796	0.643978
2015M02	0.445606	0.098210	-0.422222	0.097144	0.003131	-0.011013	-0.008060	0.085024
2015M03	0.276493	-0.794532	-0.495109	-0.878478	0.167449	0.043955	0.176134	-0.826312
2015M04	0.264155	-0.212528	0.022265	-0.039062	-0.003749	-0.030468	-0.008006	-0.211746
2015M05	0.212223	-0.571176	0.120275	0.273610	-0.022110	-0.033946	-0.047696	-0.558611
2015M06	0.126510	0.303596	-0.148223	-0.013750	-0.040396	-0.061315	-0.040360	0.294356

Note: Outliers are highlighted in red

The influence statistics indicate the presence of outliers.

1. RStudent: 4 outliers
2. DFFITS: 4 outliers
3. COVRATIO: 10 outliers
4. Hat Matrix: 30 outliers
5. DFBETAS
    - Intercept: 7 outliers
    - Inflation: 6 outliers
    - Industrial Production: 3 outliers
    - Real Interest Rate: 3 outliers
    - Risk Premium: 5 outliers
    - Term Structure: 3 outliers
    - Oil Price: 4 outliers
    - FEARS: 7 outliers

The results from the leverage plots and influence statistics indicate that model (2) possibly lacks some explanatory power more due to redundant variables, serially correlated residuals and less due to the presence of outliers.

3. India

Endogeneity tests were conducted on regression models (1) and (2) and all variables were found to be exogenous. The robustness checks on (1) can also be found in Table D1 above. The residual of (1) was found to be stationary, normally distributed and no ARCH effects were found to be present. The leverage plots and influence statistics (Figure D3 and Table D4 below) indicate outliers or serially correlated residuals could explain the lack of explanatory power of (1). Overall, (1) suffers from a redundant variables, serially correlated residuals as well as the presence of outliers. Finally, output (1) in Table C10 in Appendix C shows the result of a correlation analysis between FEARS and a volatility index for the VIX. The analysis showed that there was no statistically significant correlation between the two variables; this implies that there is no evidence for the noise trader theory, even if FEARS was found to be statistically significant.

Leverage plots and influence statistics were completed for model (1) – a macroeconomic APT model without the FEARS variable.

Figure D3: Leverage Plots - India

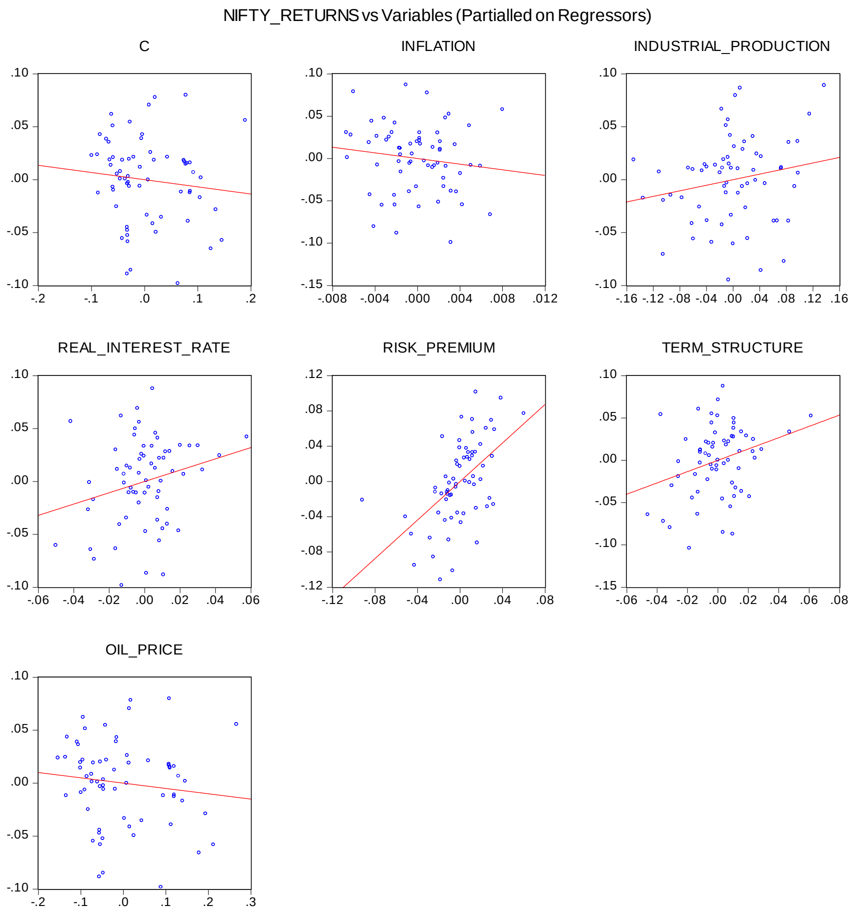

Table D4: Influence Statistics - India

Obs.	Resid.	RStudent	DFFITS	COVRATIO	Hat Matrix
2010M02	0.009029	0.239177	-0.113148	1.372563	0.182872
2010M03	0.023320	0.603642	-0.243145	1.255444	0.139596
2010M04	0.021778	0.550628	-0.182716	1.208124	0.099191
2010M05	-0.033660	-0.886970	0.392343	1.226900	0.163645
2010M06	0.020725	0.513316	-0.131862	1.165745	0.061903
2010M07	-0.006665	-0.167708	0.054245	1.243325	0.094710
2010M08	0.019787	0.532219	-0.269654	1.370993	0.204268
2010M09	0.085164	2.173956	-0.488208	0.679333	0.048011
2010M10	-0.005164	-0.128602	0.036899	1.219966	0.076063
2010M11	-0.007031	-0.174916	0.049401	1.214982	0.073872
2010M12	0.024111	0.605671	-0.186235	1.181964	0.086380
2011M01	-0.093923	-2.435300	0.611361	0.600483	0.059286
2011M02	-0.033354	-0.830778	0.219952	1.110975	0.065503
2011M03	0.071069	1.971123	-0.999615	0.894963	0.204569
2011M04	0.000214	0.005501	-0.002177	1.306439	0.135468
2011M05	-0.033245	-0.823876	0.200923	1.101475	0.056136
2011M06	0.026604	0.652698	-0.135231	1.118121	0.041160
2011M07	-0.040515	-0.993515	0.177465	1.033518	0.030920
2011M08	-0.048258	-1.231202	0.402507	1.040353	0.096558
2011M09	0.078988	2.313547	-1.405544	0.824994	0.269588
2011M10	0.011209	0.303217	-0.159129	1.424375	0.215942
2011M11	-0.091465	-2.373326	0.626420	0.624650	0.065128
2011M12	-0.087422	-2.272608	0.649581	0.665722	0.075529
2012M01	0.052468	1.364788	-0.517563	1.031507	0.125731
2012M02	-0.004657	-0.115188	0.029998	1.204100	0.063513
2012M03	0.000903	0.023237	-0.009210	1.306807	0.135765
2012M04	-0.005943	-0.151315	0.054829	1.274173	0.116060
2012M05	-0.058405	-1.488024	0.448362	0.943529	0.083233
2012M06	0.042288	1.042754	-0.212684	1.030688	0.039940
2012M07	-0.060759	-1.535943	0.409920	0.910889	0.066491
2012M08	-0.011057	-0.272728	0.067138	1.187025	0.057139
2012M09	0.057433	1.437808	-0.339664	0.929291	0.052858
2012M10	-0.047188	-1.171313	0.262769	1.004361	0.047916
2012M11	0.017301	0.434083	-0.133996	1.208836	0.086998
2012M12	-0.050138	-1.278636	0.411763	1.022716	0.093961
2013M01	-0.008217	-0.200403	0.038848	1.166142	0.036217
2013M02	-0.054911	-1.411415	0.477405	0.989656	0.102664
2013M03	-0.006758	-0.167283	0.043987	1.203415	0.064671
2013M04	0.038384	1.002238	-0.412710	1.168938	0.144985
2013M05	-0.001932	-0.047836	0.012683	1.208524	0.065682
2013M06	0.015622	0.397585	-0.142032	1.249151	0.113175
2013M07	0.001879	0.052529	-0.031704	1.540371	0.267008
2013M08	0.017564	0.601483	-0.611746	2.198251	0.508458
2013M09	0.016113	0.404045	-0.124270	1.211802	0.086421
2013M10	0.036906	0.936419	-0.306093	1.123436	0.096534
2013M11	-0.013932	-0.377916	0.200464	1.422131	0.219587
2013M12	-0.018570	-0.469653	0.157366	1.222759	0.100938
2014M01	-0.029161	-0.717479	0.156063	1.110751	0.045176
2014M02	0.014353	0.354517	-0.088715	1.181829	0.058931
2014M03	0.046748	1.207227	-0.443824	1.074426	0.119066
2014M04	-0.002444	-0.061090	0.018410	1.231470	0.083254
2014M05	0.033469	0.835757	-0.229438	1.115323	0.070083
2014M06	0.030867	0.762368	-0.177368	1.108981	0.051348
2014M07	0.009296	0.227246	-0.046751	1.169827	0.040605
2014M08	0.016968	0.419913	-0.107763	1.178100	0.061790
2014M09	0.004668	0.113964	-0.022904	1.173211	0.038823
2014M10	0.019778	0.490743	-0.130099	1.173687	0.065666

2014M11	0.019586	0.496351	-0.169244	1.223286	0.104156
2014M12	-0.009914	-0.266690	0.136401	1.412534	0.207349
2015M01	0.068816	1.892271	-0.930737	0.915700	0.194801
2015M02	-0.019342	-0.495791	0.186891	1.251677	0.124416
2015M03	-0.047643	-1.254945	0.530417	1.100013	0.151566
2015M04	-0.056931	-1.496431	0.599567	1.000883	0.138326
2015M05	0.022115	0.546382	-0.133866	1.154273	0.056628
2015M06	0.013085	0.324302	-0.086048	1.193478	0.065771

Note: Outliers are highlighted in red

Obs.	C	INFLATION	INDUSTRIAL_ PRODUCTION	REAL_INTE REST_RATE	RISK_PREMI UM	TERM_STR UCTURE	OIL_PRICE
2010M02	0.182872	0.052419	-0.016400	-0.010890	0.011025	-0.014059	0.041601
2010M03	0.139596	0.089963	0.053335	0.132393	0.088880	0.113311	0.067936
2010M04	0.099191	0.093207	0.004586	-0.134518	0.046546	-0.007397	0.036773
2010M05	0.163645	-0.148082	0.003802	0.078863	0.328848	0.146328	0.299841
2010M06	0.061903	0.078778	-0.053873	-0.015604	0.050980	0.055239	0.036832
2010M07	0.094710	-0.028175	0.011693	-0.008114	-0.039121	-0.020753	-0.034238
2010M08	0.204268	0.086276	-0.000786	-0.083550	0.103275	0.037945	0.017480
2010M09	0.048011	0.324142	-0.090779	0.049298	0.068124	0.178213	0.051884
2010M10	0.076063	-0.021534	0.003112	-0.009483	-0.020097	-0.003538	-0.020840
2010M11	0.073872	-0.023371	0.005077	0.029140	0.007659	0.012367	0.018033
2010M12	0.086380	0.051028	0.004942	0.111246	-0.001334	0.027182	-0.025577
2011M01	0.059286	-0.295599	-0.300763	0.035482	-0.181320	0.093043	-0.165219
2011M02	0.065503	-0.050982	-0.119501	0.110573	0.081566	0.010420	0.096811
2011M03	0.204569	0.036531	0.674354	0.633101	-0.059573	0.019338	0.005002
2011M04	0.135468	7.87E-05	0.001132	-0.001670	3.89E-05	-0.000107	-2.54E-07
2011M05	0.056136	-0.007462	-0.101800	0.004732	-0.074493	0.035148	-0.054247
2011M06	0.041160	0.014693	-0.060848	0.020920	-0.007490	-0.010974	-0.034252
2011M07	0.030920	-0.029403	0.030046	0.034386	-0.050681	-0.019411	-0.080455
2011M08	0.096558	-0.052289	-0.097228	0.161435	0.266111	0.297900	0.311388
2011M09	0.269588	0.100727	0.094514	0.021022	-0.763237	-1.334131	-0.682787
2011M10	0.215942	-0.005364	-0.059349	-0.001910	0.134004	0.110588	0.141330
2011M11	0.065128	0.148842	0.182870	-0.215357	0.212514	0.241303	0.308543
2011M12	0.075529	0.113410	0.369633	-0.379603	-0.017872	-0.205268	-0.055716
2012M01	0.125731	-0.073927	0.146712	-0.031650	-0.051194	0.302003	-0.001048
2012M02	0.063513	0.006727	-0.012153	0.003159	-0.007448	-0.019356	-0.005601
2012M03	0.135765	-0.001422	0.005647	0.003775	0.002705	-0.001602	0.002420
2012M04	0.116060	0.009656	-0.009847	0.035156	0.009609	0.007964	0.000766
2012M05	0.083233	0.121308	0.124747	-0.070846	0.298804	0.209636	0.328992
2012M06	0.039940	-0.007852	-0.127217	-0.008772	0.045329	0.068918	0.075552
2012M07	0.066491	0.093018	0.202108	-0.000815	-0.090724	-0.269204	-0.090255
2012M08	0.057139	0.031209	-0.043264	0.006137	-0.000449	-0.013596	0.001474
2012M09	0.052858	-0.170710	0.167201	-0.022498	-0.029228	0.092835	-0.039219
2012M10	0.047916	0.072523	0.099032	-0.154354	-0.103917	-0.098651	-0.126308
2012M11	0.086998	-0.024446	-0.108445	-0.025180	0.025944	0.035508	0.021507
2012M12	0.093961	0.080912	0.228480	-0.234266	-0.093580	-0.203302	-0.098821
2013M01	0.036217	0.010815	-0.011009	-0.005901	0.006515	-0.013854	0.004864
2013M02	0.102664	0.088780	-0.388862	0.099546	0.163915	0.084326	0.132849
2013M03	0.064671	0.002889	-0.006798	-0.035392	-0.002818	0.007366	-0.004766
2013M04	0.144985	-0.011108	-0.087252	-0.337894	-0.118565	-0.001561	-0.151979
2013M05	0.065682	0.003376	-0.001215	0.000943	0.009626	0.003112	0.008631
2013M06	0.113175	-0.032818	0.023526	-0.005232	-0.088850	-0.115955	-0.073245
2013M07	0.267008	-0.005884	-0.003724	0.009346	0.017615	-0.003692	0.019465
2013M08	0.508458	-0.141800	0.009352	-0.108075	0.175232	-0.105567	-0.019464
2013M09	0.086421	-0.078309	-0.010141	0.037237	0.031254	0.026486	0.053393
2013M10	0.096534	-0.153542	-0.161518	0.061724	0.050147	0.156990	0.071216
2013M11	0.219587	0.046600	0.061179	-0.007023	-0.023271	0.045961	-0.070463

2013M12	0.100938	0.080251	0.029161	-0.095805	0.010396	-0.035942	0.022137
2014M01	0.045176	0.072384	-0.069134	-0.029471	0.050653	0.054719	0.063796
2014M02	0.058931	-0.044510	0.029705	-0.035425	0.010005	0.018595	0.013740
2014M03	0.119066	-0.142939	0.239025	0.309797	-0.048710	-0.002103	-0.034357
2014M04	0.083254	0.005451	-0.004699	0.012455	0.003286	0.001316	0.001933
2014M05	0.070083	-0.115836	0.062812	0.031420	-0.002090	0.114105	-0.009536
2014M06	0.051348	-0.097913	0.006263	0.003280	0.022591	0.025348	0.054744
2014M07	0.040605	-0.027213	-0.015045	0.003584	-0.004786	-0.007428	-0.008904
2014M08	0.061790	-0.047331	-0.047885	-0.035457	-0.023502	6.10E-05	-0.033627
2014M09	0.038823	-0.009858	-0.002190	0.007515	-0.009025	-0.010667	-0.009096
2014M10	0.065666	-0.019351	-0.073781	-0.044836	-0.034062	0.018837	-0.038690
2014M11	0.104156	0.017705	-0.133486	0.039323	-0.054368	-0.037225	-0.040579
2014M12	0.207349	-0.058521	0.075340	-0.030116	0.064311	0.073473	0.061016
2015M01	0.194801	0.745885	-0.482633	-0.074268	-0.188648	-0.186199	-0.179194
2015M02	0.124416	-0.132622	-0.049499	0.055727	-0.026605	-0.055663	-0.049675
2015M03	0.151566	-0.370395	-0.218494	-0.188552	-0.005598	-0.006269	-0.027716
2015M04	0.138326	-0.376124	-0.009058	0.354280	-0.209783	-0.224056	-0.225838
2015M05	0.056628	0.078678	0.075765	-0.008775	-0.010004	0.012218	-0.010789
2015M06	0.065771	0.057791	0.027272	-0.011223	-0.026434	-0.041879	-0.018007

Note: Outliers are highlighted in red

The influence statistics indicate the presence of outliers.

1. RStudent: 5 outliers
2. DFFITS: 3 outliers
3. COVRATIO: 10 outliers
4. Hat Matrix: 27 outliers
5. DFBETAS
    - Intercept: 3 outliers
    - Inflation: 5 outliers
    - Industrial Production: 5 outliers
    - Real Interest Rate: 5 outliers
    - Risk Premium: 4 outliers
    - Term Structure: 4 outliers
    - Oil Price: 5 outliers

The results from the leverage plots and influence statistics indicate that model (1) lacks explanatory power, possibly due to the number of outliers as the risk premium variable which is consistently statistically significant has the fewest number of outliers or due to the fact that the residuals are serially correlated.

4. China

Endogeneity tests were conducted on regression models (1) and (2) and all variables were found to be exogenous. The robustness checks on (1) can also be found in Table D1 above. The residual of (1) was found to be stationary, normally distributed and no ARCH effects were found to be present. The leverage plots and influence statistics (Figure D4 and Table D5 below) are consistent with the regression results and indicate that outliers are not necessarily the reason behind (1)'s poor explanatory power. Overall, (1) suffers from serially correlated residuals, but not redundant variables or outliers.

Leverage plots and influence statistics were completed for model (1) – a macroeconomic APT model without the FEARS variable.

Figure D4: Leverage Plots - China

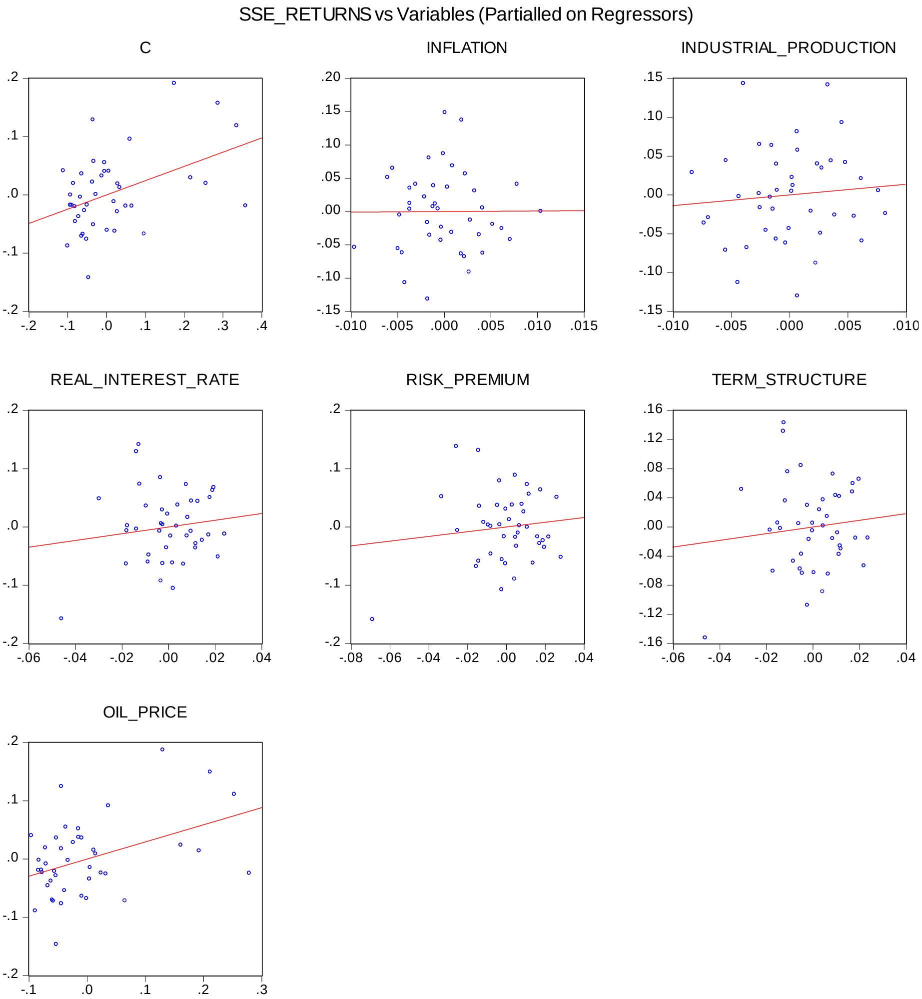

Table D5: Influence Statistics - China

Obs.	Resid.	RStudent	DFFITS	COVRATIO	Hat Matrix
2012M01	0.040272	0.706930	-0.398482	1.457447	0.241122
2012M02	0.051699	0.938763	-0.589691	1.428150	0.282939
2012M03	-0.062975	-1.020402	0.331285	1.096335	0.095354
2012M04	0.068537	1.097495	-0.299756	1.031658	0.069420
2012M05	0.003873	0.062848	-0.023745	1.398684	0.124913
2012M06	-0.055255	-0.926190	0.402825	1.223531	0.159071
2012M07	-0.063597	-1.062116	0.439709	1.141816	0.146314
2012M08	-0.026049	-0.435189	0.196752	1.419083	0.169711
2012M09	0.007279	0.115681	-0.035767	1.338375	0.087255
2012M10	-0.035469	-0.594683	0.270722	1.375499	0.171665
2012M11	-0.067912	-1.117433	0.407781	1.078385	0.117521
2012M12	0.137279	2.364293	-0.767408	0.466539	0.095312
2013M01	0.035291	0.564489	-0.178402	1.262151	0.090812
2013M02	-0.000670	-0.011463	0.005976	1.557812	0.213684
2013M03	-0.052962	-0.905101	0.441053	1.283142	0.191892
2013M04	-0.019942	-0.323571	0.120577	1.365364	0.121931
2013M05	0.041300	0.656120	-0.187259	1.213059	0.075320
2013M06	-0.131192	-3.077038	2.865306	0.409683	0.464414
2013M07	-0.031292	-0.515071	0.210191	1.353291	0.142758
2013M08	0.038904	0.690294	-0.406772	1.497130	0.257743
2013M09	0.030719	0.487003	-0.140355	1.263699	0.076690
2013M10	-0.013106	-0.206866	0.058397	1.310988	0.073807
2013M11	0.011653	0.184216	-0.053170	1.317778	0.076900
2013M12	-0.061470	-1.013074	0.384533	1.138070	0.125931
2014M01	-0.043213	-0.673164	0.133205	1.160258	0.037681
2014M02	0.022187	0.358951	-0.130163	1.349824	0.116212
2014M03	0.005172	0.082773	-0.027585	1.359097	0.099962
2014M04	-0.005037	-0.086123	0.044595	1.551039	0.211434
2014M05	-0.035242	-0.638430	0.407382	1.585781	0.289354
2014M06	0.012488	0.203600	-0.079361	1.399099	0.131897
2014M07	0.056475	0.914743	-0.304846	1.148023	0.099960
2014M08	-0.016321	-0.257231	0.070811	1.299980	0.070442
2014M09	0.065593	1.112988	-0.504431	1.149393	0.170407
2014M10	0.004294	0.068378	-0.021624	1.346173	0.090914
2014M11	0.080615	1.333438	-0.477426	0.967259	0.113628
2014M12	0.148832	2.825563	-1.458830	0.354430	0.210461
2015M01	-0.106531	-2.190409	1.707402	0.781625	0.377956
2015M02	-0.042854	-0.752254	0.422336	1.435273	0.239659
2015M03	0.036544	0.655865	-0.404425	1.548300	0.275484
2015M04	0.086768	1.544285	-0.823571	0.978902	0.221433
2015M05	-0.023684	-0.397118	0.183858	1.440124	0.176515
2015M06	-0.091001	-1.863191	1.502725	1.023728	0.394121

Note: Outliers are highlighted in red

Obs.	C	INFLATION	INDUSTRIAL_ PRODUCTION	REAL_INTE REST_RATE	RISK_PREMI UM	TERM_STR UCTURE	OIL_PRICE
2012M01	0.241122	-0.089369	0.241163	-0.260386	0.157253	0.186370	0.151189
2012M02	0.282939	-0.091588	-0.256032	-0.231955	0.229464	0.114626	0.209521
2012M03	0.095354	0.139224	-0.168725	0.151252	-0.020612	0.004199	-0.005577
2012M04	0.069420	-0.163846	0.038042	-0.112284	0.094257	0.107379	0.108002
2012M05	0.124913	-0.007784	-0.009437	-0.011228	-0.013047	-0.014884	-0.013552
2012M06	0.159071	0.083287	0.190117	0.045158	0.096490	0.019475	0.060912
2012M07	0.146314	0.076197	-0.079189	0.242546	-0.266824	-0.285562	-0.276416

2012M08	0.169711	0.049559	-0.112261	0.134609	-0.125253	-0.092079	-0.123926
2012M09	0.087255	-0.004236	-0.005547	-0.004953	-0.004121	-0.009993	-0.008116
2012M10	0.171665	-0.023592	0.038564	-0.206203	-0.083567	-0.099122	-0.086269
2012M11	0.117521	-0.033203	-0.097834	-0.282957	-0.083446	-0.144530	-0.085356
2012M12	0.095312	-0.111899	0.178504	0.312841	-0.372459	-0.314554	-0.347062
2013M01	0.090812	-0.009221	-0.083008	0.108715	0.025577	0.041795	0.028369
2013M02	0.213684	0.001356	-0.005090	0.000825	-0.000484	-0.000774	-0.000633
2013M03	0.191892	0.078874	0.369075	-0.102549	0.198562	0.126139	0.189510
2013M04	0.121931	0.031966	-0.068249	0.092267	-0.029946	-0.014498	-0.032216
2013M05	0.075320	-0.004085	-0.079487	-0.029457	-0.071394	-0.083609	-0.088623
2013M06	0.464414	0.247906	0.284110	-0.107158	2.097942	2.556824	2.130834
2013M07	0.142758	-0.035859	-0.016764	-0.082368	-0.087630	-0.092867	-0.071128
2013M08	0.257743	0.006484	-0.035102	0.109248	0.085974	-0.032439	0.085754
2013M09	0.076690	-0.023606	0.062562	0.053860	-0.014468	-0.001073	-0.013151
2013M10	0.073807	0.015714	-0.022710	0.020850	-0.022521	-0.011541	-0.024993
2013M11	0.076900	0.007192	-0.007107	0.002067	0.017246	0.002540	0.012891
2013M12	0.125931	-0.002580	0.185768	0.013973	0.029241	0.147990	0.054517
2014M01	0.037681	0.029772	0.009637	0.001824	0.063370	0.048093	0.063185
2014M02	0.116212	-0.045696	-0.030819	0.003022	-0.001541	0.030582	0.011717
2014M03	0.099962	-0.010491	0.013631	-0.008763	-0.002342	-0.002598	-0.000120
2014M04	0.211434	0.006279	0.017632	-0.028330	0.003989	-0.009206	0.000214
2014M05	0.289354	-0.064597	-0.107971	-0.160464	0.007256	-0.035322	0.040698
2014M06	0.131897	-0.018994	-0.030543	0.051469	-0.042011	-0.022426	-0.036152
2014M07	0.099960	-0.005971	0.082124	0.025780	0.204112	0.150458	0.208632
2014M08	0.070442	-0.006606	0.018269	0.014642	-0.002633	0.002809	0.005092
2014M09	0.170407	-0.051730	-0.257237	-0.071665	-0.396418	-0.359107	-0.410359
2014M10	0.090914	0.003193	-0.001843	0.000486	-0.010786	-0.005065	-0.010954
2014M11	0.113628	0.111240	-0.087713	0.034621	-0.191255	-0.042989	-0.168131
2014M12	0.210461	0.719456	0.010547	-0.484535	-0.439332	-0.723055	-0.434363
2015M01	0.377956	-1.290295	0.445603	0.474102	-0.059187	0.058651	0.070553
2015M02	0.239659	-0.286222	-0.232305	0.067446	-0.109707	-0.149071	-0.105638
2015M03	0.275484	0.335067	0.009597	0.070516	0.105567	0.020351	0.096500
2015M04	0.221433	0.651804	-0.007018	0.301085	-0.065421	0.071317	-0.098895
2015M05	0.176515	-0.123058	0.005054	-0.030853	-0.082205	-0.062245	-0.088158
2015M06	0.394121	-0.301512	-0.241895	-0.206205	0.085049	-0.088974	-0.109168

Note: Outliers are highlighted in red

The influence statistics indicate the presence of outliers.

1. RStudent: 4 outliers
2. DFFITS: 5 outliers
3. COVRATIO: 7 outliers
4. Hat Matrix: 19 outliers
5. DFBETAS
    - Intercept: 3 outliers
    - Inflation: 4 outliers
    - Industrial Production: 2 outliers
    - Real Interest Rate: 3 outliers
    - Risk Premium: 4 outliers
    - Term Structure: 4 outliers

- Oil Price: 4 outliers

The results from the leverage plots and influence statistics indicate that model (1) lacks explanatory power. However, outliers do not appear to be the reason behind this as there are very few outliers for each variable.

5. South Africa

Endogeneity tests were conducted on regression models (1) and (2) and all variables were found to be exogenous. The robustness checks on (2) can also be found in Table D1 above. The residual of (2) was found to be stationary, normally distributed and no ARCH effects were found to be present. The leverage plots and influence statistics (Figure D5 and Table D6 below) are consistent with the regression results and show that the number of outliers is not necessarily related to those variables found to be statistically significant. Overall, (2) suffers from serially correlated residuals, but not from redundant variables of the presence of outliers. Finally, output (2) in Table C10 in Appendix C shows the result of a correlation analysis between FEARS and the SAVI. This relationship is found to be positively and statistically significantly correlated at the 5% level of significance; this implies that the regression result could provide support for the noise trader hypothesis (De Long, Shleifer, Summers, & Waldmann, 1990) and is not necessarily a true explanatory relationship.

Leverage plots and influence statistics were completed for model (2) – a macroeconomic APT model with the FEARS variable included.

Figure D5: Leverage Plots - South Africa

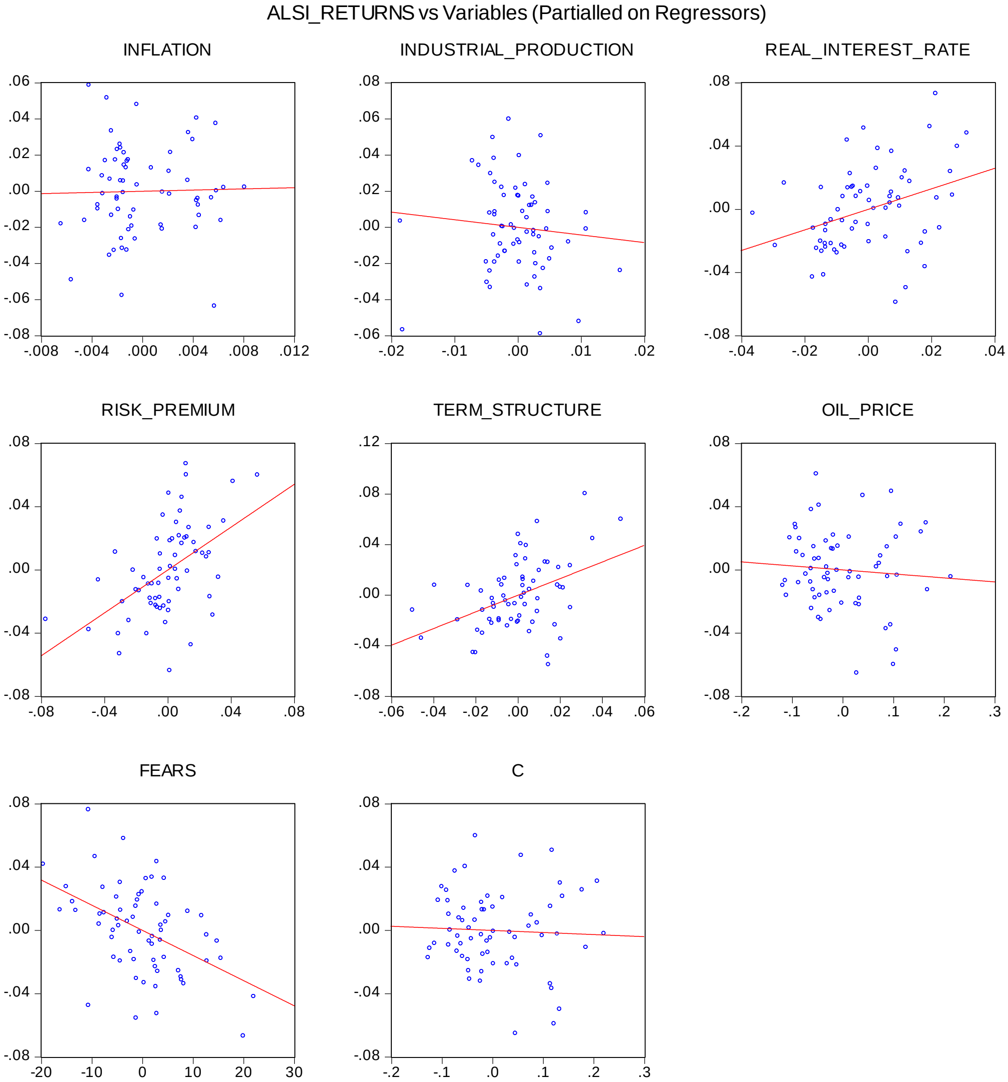

Table D6: Influence Statistics - South Africa

Obs.	Resid.	RStudent	DFFITS	COVRATIO	Hat Matrix
2010M02	-0.002069	-0.080722	0.018921	1.214279	0.052080
2010M03	0.010654	0.444011	-0.198450	1.343942	0.166503
2010M04	-0.017107	-0.733330	0.375166	1.346650	0.207435
2010M05	-0.032369	-1.303153	0.391887	0.989235	0.082934
2010M06	-0.048061	-2.045194	0.838371	0.756267	0.143862
2010M07	0.031764	1.320432	-0.530964	1.047283	0.139189
2010M08	-0.035091	-1.492959	0.678766	1.017393	0.171295
2010M09	0.052153	2.162046	-0.682139	0.667060	0.090532
2010M10	0.005891	0.234885	-0.074556	1.258237	0.091530
2010M11	0.016677	0.676308	-0.244517	1.220635	0.115605
2010M12	0.048053	1.945352	-0.492774	0.726616	0.060296
2011M01	-0.064524	-3.116163	1.915468	0.441694	0.274227
2011M02	0.003566	0.150444	-0.072697	1.416542	0.189298
2011M03	-0.004730	-0.193637	0.077731	1.330622	0.138780
2011M04	0.012668	0.506963	-0.164375	1.227435	0.095128
2011M05	-0.021174	-0.823596	0.156639	1.084166	0.034909

2011M06	-0.021205	-0.827215	0.169968	1.089572	0.040508
2011M07	-0.020761	-0.817908	0.205540	1.113861	0.059400
2011M08	-0.003914	-0.161406	0.068201	1.352769	0.151493
2011M09	0.021048	0.931166	-0.539798	1.361244	0.251527
2011M10	0.021501	0.891109	-0.371718	1.208496	0.148216
2011M11	0.014726	0.591946	-0.199041	1.219952	0.101579
2011M12	-0.007001	-0.292127	0.132316	1.371660	0.170230
2012M01	-0.004480	-0.198395	0.118824	1.556614	0.264009
2012M02	-0.026416	-1.055181	0.306704	1.067378	0.077904
2012M03	-0.017289	-0.698105	0.242346	1.204497	0.107551
2012M04	0.013184	0.510101	-0.092477	1.146655	0.031821
2012M05	-0.015349	-0.609793	0.179766	1.187662	0.079957
2012M06	-0.014062	-0.559760	0.170048	1.203499	0.084490
2012M07	-0.000590	-0.023350	0.006878	1.251967	0.079830
2012M08	-0.009229	-0.367884	0.115674	1.241804	0.089971
2012M09	-0.005839	-0.228587	0.056574	1.213594	0.057718
2012M10	0.012831	0.499228	-0.105639	1.161689	0.042858
2012M11	-0.003008	-0.117269	0.027016	1.210875	0.050397
2012M12	0.005982	0.234417	-0.059039	1.215614	0.059646
2013M01	0.017649	0.714032	-0.251781	1.204769	0.110589
2013M02	-0.014135	-0.562834	0.171600	1.203645	0.085049
2013M03	0.000940	0.037617	-0.012417	1.277396	0.098260
2013M04	-0.031366	-1.256184	0.358260	0.997488	0.075219
2013M05	0.059317	2.925500	-1.989761	0.540123	0.316284
2013M06	-0.019124	-0.776829	0.281814	1.196603	0.116300
2013M07	0.036559	1.480302	-0.453128	0.926901	0.085673
2013M08	0.024181	0.956673	-0.248639	1.080335	0.063274
2013M09	0.017552	0.699746	-0.212443	1.173653	0.084394
2013M10	0.009026	0.355217	-0.094839	1.212213	0.066539
2013M11	-0.026049	-1.071145	0.412860	1.125083	0.129346
2013M12	-0.012949	-0.527113	0.199269	1.265645	0.125042
2014M01	-0.018990	-0.811131	0.405517	1.311603	0.199962
2014M02	0.039716	1.737780	-0.884766	0.953046	0.205857
2014M03	-0.000812	-0.032932	0.012371	1.314489	0.123665
2014M04	0.026297	1.051760	-0.310904	1.071309	0.080360
2014M05	0.006975	0.287031	-0.119149	1.334846	0.146987
2014M06	-0.009705	-0.383121	0.106632	1.215634	0.071895
2014M07	0.005339	0.211489	-0.062322	1.244185	0.079898
2014M08	-0.010369	-0.408512	0.110191	1.206864	0.067824
2014M09	-0.032491	-1.336161	0.492896	1.018280	0.119780
2014M10	0.017374	0.692456	-0.209822	1.174956	0.084095
2014M11	-0.000804	-0.031976	0.009983	1.264224	0.088814
2014M12	0.023337	0.985220	-0.456243	1.219462	0.176582
2015M01	0.033782	1.578539	-1.057801	1.178484	0.309894
2015M02	0.027930	1.250002	-0.740334	1.248722	0.259687
2015M03	0.000929	0.042071	-0.027277	1.636014	0.295959
2015M04	-0.008416	-0.359365	0.183599	1.426305	0.206989
2015M05	-0.057431	-2.362515	0.610134	0.574697	0.062526
2015M06	-0.000693	-0.027151	0.006893	1.226238	0.060549

Note: Outliers are highlighted in red

Obs.	INFLATION	INDUSTRIAL_PRODUCTION	REAL_INTEREST_RATE	RISK_PREMIUM	TERM_STRUCTURE	OIL_PRICE	FEARS	C
2010M02	0.052080	-0.006528	-0.002720	0.005772	0.004719	0.006581	-0.011627	0.000790
2010M03	0.166503	0.037858	0.052464	-0.015738	0.024766	0.008559	0.057313	-0.143721
2010M04	0.207435	0.196300	-0.301901	0.103500	-0.032603	-0.005155	-0.042992	0.029063
2010M05	0.082934	0.062865	-0.110894	0.164359	0.237588	0.190494	-0.204292	0.024277
2010M06	0.143862	0.461005	-0.483574	-0.341193	-0.360431	-0.313678	-0.371705	-0.095088

2010M07	0.139189	0.192001	-0.199524	0.090924	0.064255	-0.009084	0.259573	-0.200870
2010M08	0.171295	0.158875	0.161938	-0.177132	-0.250156	-0.201732	-0.222059	-0.492142
2010M09	0.090532	-0.235906	0.187093	-0.026598	0.153163	0.146117	0.346294	-0.127341
2010M10	0.091530	-0.013723	0.007865	-0.020106	0.006734	0.004172	0.028099	-0.016005
2010M11	0.115605	-0.032311	-0.035327	0.071942	0.030050	0.071164	0.099915	0.160026
2010M12	0.060296	-0.033718	-0.180102	-0.114057	0.007681	0.001831	0.125697	0.085780
2011M01	0.274227	-0.770443	1.512561	-0.274004	-0.025366	-0.370434	-0.160006	0.589025
2011M02	0.189298	-0.002723	0.040854	0.009872	-0.004534	-0.007809	0.017532	-0.038035
2011M03	0.138780	-0.033782	-0.037795	0.024057	0.006778	0.006311	-0.003938	-0.004227
2011M04	0.095128	-0.083805	0.130507	-0.010931	0.036857	0.008841	-0.016060	0.036881
2011M05	0.034909	0.033552	-0.075936	0.070500	0.012260	0.029140	0.002628	0.021249
2011M06	0.040508	-0.048906	0.095319	-0.040733	0.022796	0.001460	-0.043677	-0.038066
2011M07	0.059400	-0.131999	0.070512	-0.001932	-0.004297	-0.001149	-0.034530	-0.103711
2011M08	0.151493	0.013039	-0.013443	0.044157	0.050004	0.056140	-0.008805	0.036583
2011M09	0.251527	0.088711	-0.062197	-0.336268	-0.475259	-0.376266	0.021645	0.046433
2011M10	0.148216	-0.052403	-0.006835	0.233333	0.313744	0.240054	-0.028627	-0.010057
2011M11	0.101579	-0.033243	0.038816	-0.001156	-0.078254	-0.075950	-0.009711	-0.073705
2011M12	0.170230	0.041836	0.000132	-0.059711	-0.048052	-0.045093	0.014556	-0.106355
2012M01	0.264009	-0.046701	0.097432	-0.019739	-0.029261	-0.030392	0.026765	0.016362
2012M02	0.077904	0.023077	-0.067010	-0.212744	-0.201501	-0.191902	0.044070	0.072903
2012M03	0.107551	-0.169870	0.051839	0.052843	0.031869	0.015615	0.053575	-0.085023
2012M04	0.031821	-0.024604	0.025713	-0.035478	-0.013781	-0.028008	-0.047053	-0.010163
2012M05	0.079957	0.107503	-0.072364	0.073332	0.089130	0.084662	0.031316	-0.021848
2012M06	0.084490	0.020490	0.027384	0.081760	0.016892	0.050607	0.015590	0.053289
2012M07	0.079830	0.001370	0.001390	-0.001440	-0.002490	-0.000516	0.000453	-0.001298
2012M08	0.089971	0.050356	-0.046763	0.016464	-0.027247	-0.025621	0.038744	0.033569
2012M09	0.057718	-0.037359	0.020463	0.007798	-0.000860	0.002389	0.013507	-0.006719
2012M10	0.042858	0.013271	0.021442	0.047181	0.031434	0.036227	-0.017891	-0.039517
2012M11	0.050397	0.008949	-0.006793	-0.005857	-0.003324	-0.001435	0.005627	0.015241
2012M12	0.059646	-0.015457	-0.024424	0.015217	0.022980	0.012762	-0.018032	0.013646
2013M01	0.110589	-0.060244	0.040097	-0.041568	0.057848	0.068673	-0.102761	0.059163
2013M02	0.085049	-0.097560	0.026674	0.059143	0.035527	0.036854	0.054811	-0.063228
2013M03	0.098260	0.009418	-0.000923	-0.003992	-0.004542	-0.003225	-0.002005	-0.001790
2013M04	0.075219	0.077705	-0.044092	0.197423	0.098657	0.193919	0.099613	-0.052417
2013M05	0.316284	-0.554673	-0.115053	0.647742	0.233327	0.789043	-0.295056	-0.571272
2013M06	0.116300	0.025649	-0.003987	0.052466	0.148023	0.097592	0.071832	-0.096022
2013M07	0.085673	0.332547	-0.133054	0.040302	-0.025393	0.042617	-0.153275	0.043898
2013M08	0.063274	-0.062987	0.026193	0.021530	-0.037796	-0.002906	-0.145022	-0.001342
2013M09	0.084394	-0.030800	-0.000291	-0.029589	0.012420	-0.045063	-0.121392	-0.011263
2013M10	0.066539	-0.043398	0.006361	0.041572	0.055069	0.049691	-0.053317	0.020000
2013M11	0.129346	0.070822	0.114886	-0.177773	-0.003268	-0.056814	0.112816	0.098125
2013M12	0.125042	0.050807	-0.033862	0.065653	0.024789	0.035289	0.106018	0.138443
2014M01	0.199962	-0.049157	-0.057620	0.082466	0.034698	-0.058377	0.160397	-0.034390
2014M02	0.205857	0.309416	0.009058	0.326145	0.100618	0.018578	-0.146101	0.125637
2014M03	0.123665	-0.007628	-0.001983	0.004027	0.003655	0.004130	0.003499	0.002631
2014M04	0.080360	-0.072125	0.117714	-0.053512	0.034910	0.028081	-0.163779	0.148099
2014M05	0.146987	-0.029573	-0.025513	0.069228	0.062788	0.053985	-0.038783	0.072698
2014M06	0.071895	0.028123	0.005736	-5.77E-05	-0.013499	-0.009456	0.071661	0.051426
2014M07	0.079898	0.029197	-0.018306	0.000656	-0.019060	-0.018840	-0.019473	-0.006007
2014M08	0.067824	0.010612	0.026630	0.054713	0.027075	0.039752	0.058791	-0.027365
2014M09	0.119780	0.117681	0.158239	-0.205981	0.011498	-0.054020	0.097839	-0.007087
2014M10	0.084095	-0.078681	0.002470	-0.031763	0.006053	-0.031741	-0.037897	0.138588
2014M11	0.088814	0.003901	0.000425	0.004981	0.005499	0.006691	-0.000780	0.003819
2014M12	0.176582	-0.079727	-0.088980	-0.137808	-0.272148	-0.180641	0.181402	-0.071802
2015M01	0.309894	-0.172344	-0.310404	-0.431730	-0.360168	-0.525330	0.495697	0.020638
2015M02	0.259687	0.214236	-0.141474	0.388789	0.342233	0.496516	0.357163	0.256158
2015M03	0.295959	0.014990	0.005186	0.004111	0.000474	0.001918	0.016990	0.009638
2015M04	0.206989	-0.065921	-0.002353	-0.092403	-0.056343	-0.060706	-0.106983	0.080205
2015M05	0.062526	0.145318	-0.196571	-0.249415	-0.206286	-0.240002	-0.387426	0.046386
2015M06	0.060549	-0.001634	0.001503	-0.000431	0.001970	0.001140	-0.004757	-0.000824

Note: Outliers are highlighted in red

The influence statistics indicate the presence of outliers.

1. RStudent: 5 outliers
2. DFFITS: 6 outliers
3. COVRATIO: 8 outliers
4. Hat Matrix: 26 outliers
5. DFBETAS
    - Intercept: 4 outliers
    - Inflation: 7 outliers
    - Industrial Production: 5 outliers
    - Real Interest Rate: 4 outliers
    - Risk Premium: 8 outliers
    - Term Structure: 7 outliers
    - Oil Price: 6 outliers
    - FEARS: 7 outliers

The results from the leverage plots and influence statistics indicate that model (2) has strong explanatory power. The number of outliers does not appear to be correlated to explanatory power as those variables found to explain Alsi returns do not necessarily have the least amount of outliers.

6. Germany

Endogeneity tests were conducted on regression models (1) and (2) and all variables were found to be exogenous. The robustness checks on (2) can also be found in Table D1 above. The residual of (2) was found to be stationary, non-normal and no ARCH effects were found to be present. The leverage plots and influence statistics (Figure D6 and Table D7 below) demonstrate a similar picture as the regression results and indicate that outliers are not a source of concern in this instance. Overall, (2) suffers from serially correlated residuals but does not necessarily lack explanatory power.

Leverage plots and influence statistics were completed for model (2) – a macroeconomic APT model with the FEARS variable included.

Figure D6: Leverage Plots - Germany

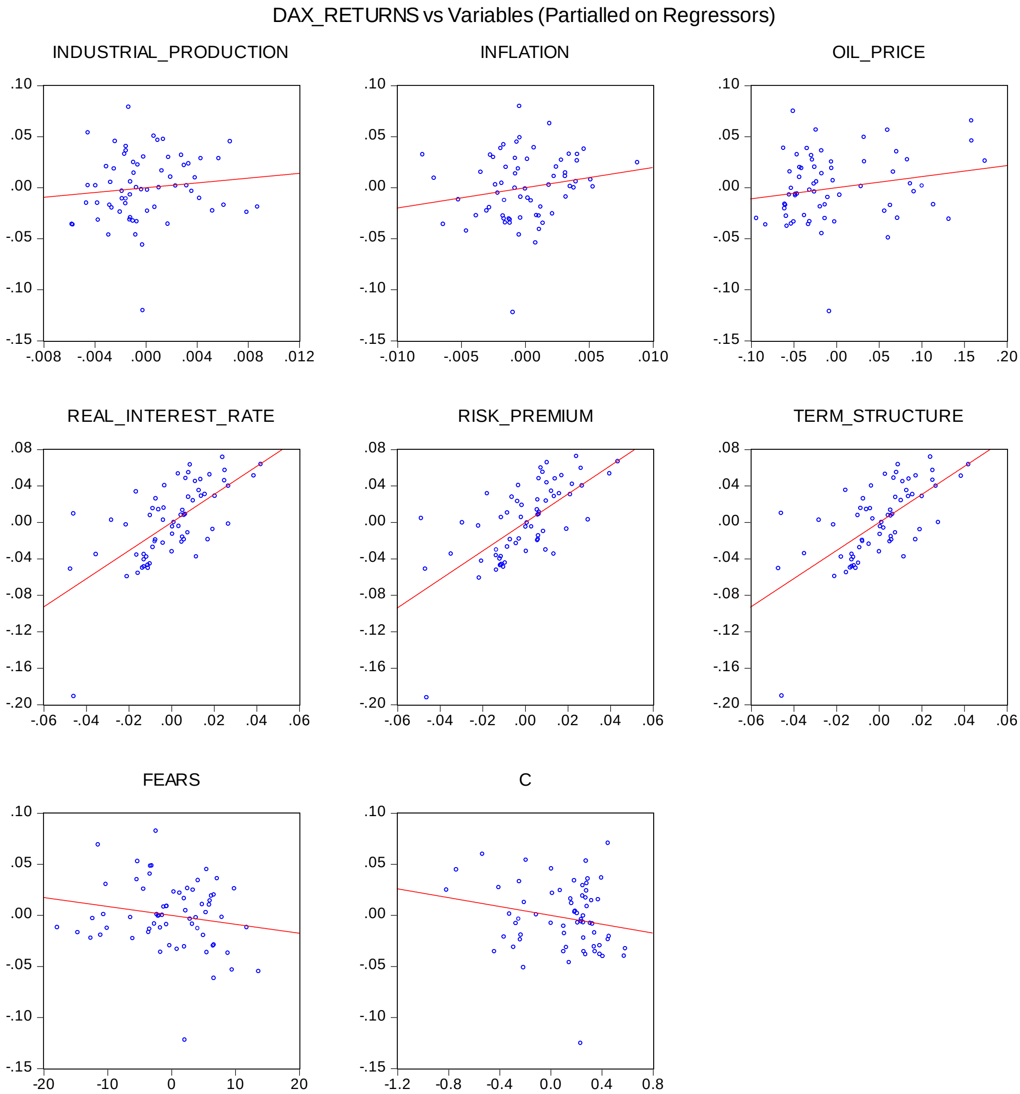

Table D7: Influence Statistics - Germany

Obs.	Resid.	RStudent	DFFITS	COVRATIO	Hat Matrix
2010M02	-0.005771	-0.172580	0.046498	1.230500	0.067679
2010M03	0.018164	0.556803	-0.193992	1.236139	0.108245
2010M04	-0.029252	-0.919101	0.375610	1.192756	0.143111
2010M05	0.021744	0.691743	-0.312538	1.296010	0.169528
2010M06	-0.024428	-0.743519	0.236039	1.172374	0.091555
2010M07	-0.037749	-1.145354	0.322727	1.033295	0.073555
2010M08	-0.055846	-1.710288	0.451244	0.820018	0.065082
2010M09	0.007984	0.237771	-0.059730	1.214970	0.059360
2010M10	0.027495	0.819066	-0.187352	1.102220	0.049720
2010M11	0.045708	1.389518	-0.372916	0.941739	0.067187
2010M12	-0.002051	-0.061640	0.017854	1.248093	0.077403
2011M01	-0.033523	-1.117273	0.615874	1.259294	0.233043
2011M02	-0.007844	-0.238602	0.078836	1.267542	0.098425
2011M03	-0.015494	-0.471265	0.153234	1.234213	0.095616
2011M04	0.037275	1.155826	-0.411752	1.075157	0.112616
2011M05	-0.032547	-0.958785	0.150160	1.036211	0.023941

2011M06	0.030113	0.893945	-0.184681	1.072546	0.040933
2011M07	-0.028962	-0.874925	0.247982	1.116558	0.074360
2011M08	-0.120345	-4.373983	1.863526	0.129674	0.153630
2011M09	0.019381	0.603145	-0.237233	1.263191	0.133978
2011M10	-0.008653	-0.279813	0.140795	1.427762	0.202034
2011M11	0.080329	2.676480	-1.138953	0.519455	0.153321
2011M12	-0.043166	-1.465280	0.843847	1.135453	0.249054
2012M01	-0.001207	-0.037763	0.015812	1.353821	0.149166
2012M02	-0.002635	-0.080468	0.027721	1.287655	0.106091
2012M03	0.004897	0.149454	-0.051199	1.283220	0.105031
2012M04	-0.020008	-0.601734	0.168440	1.179954	0.072664
2012M05	-0.031579	-0.979243	0.359074	1.141021	0.118522
2012M06	0.007289	0.227697	-0.093837	1.337840	0.145179
2012M07	0.021160	0.645018	-0.210842	1.201894	0.096535
2012M08	-0.001254	-0.037103	0.008382	1.210672	0.048557
2012M09	0.014805	0.437918	-0.094253	1.172959	0.044272
2012M10	-0.028169	-0.838486	0.187581	1.094854	0.047663
2012M11	-0.001339	-0.039451	0.008096	1.200366	0.040413
2012M12	0.006366	0.189342	-0.046676	1.215885	0.057289
2013M01	0.023221	0.730704	-0.307406	1.256890	0.150373
2013M02	-0.009771	-0.321432	0.174929	1.471479	0.228499
2013M03	0.008197	0.258630	-0.113652	1.361527	0.161852
2013M04	-0.001599	-0.049729	0.019973	1.337496	0.138910
2013M05	0.059002	2.071665	-1.267072	0.876890	0.272240
2013M06	-0.010834	-0.371761	0.237894	1.592177	0.290522
2013M07	0.024289	0.757124	-0.297303	1.225714	0.133594
2013M08	-0.027499	-0.874500	0.388316	1.237446	0.164700
2013M09	0.045200	1.357275	-0.295979	0.931573	0.045395
2013M10	0.034521	1.054590	-0.330321	1.080974	0.089343
2013M11	0.037764	1.122305	-0.214445	0.999512	0.035224
2013M12	0.015345	0.458238	-0.117755	1.191964	0.061945
2014M01	-0.023350	-0.719863	0.259653	1.209511	0.115125
2014M02	0.025779	0.771690	-0.195257	1.126403	0.060169
2014M03	-0.029922	-0.931732	0.355759	1.167220	0.127240
2014M04	-0.014069	-0.427133	0.136723	1.237534	0.092938
2014M05	0.041991	1.265759	-0.310133	0.974561	0.056633
2014M06	-0.021547	-0.646860	0.175307	1.165230	0.068422
2014M07	-0.030049	-0.900425	0.224460	1.090778	0.058506
2014M08	0.000898	0.026749	-0.006763	1.225637	0.060085
2014M09	0.022845	0.673797	-0.126973	1.118396	0.034293
2014M10	-0.016733	-0.508756	0.164204	1.226054	0.094343
2014M11	0.049572	1.497065	-0.342367	0.885718	0.049701
2014M12	-0.029160	-0.956811	0.498245	1.286344	0.213320
2015M01	0.048098	1.942015	-1.772289	1.253649	0.454400
2015M02	0.006998	0.232422	-0.131974	1.511870	0.243811
2015M03	0.028486	0.974954	-0.602751	1.391848	0.276523
2015M04	-0.045316	-1.644382	1.171237	1.190869	0.336572
2015M05	-0.013915	-0.424736	0.143691	1.251357	0.102698
2015M06	-0.009329	-0.302847	0.155137	1.435525	0.207867

Note: Outliers are highlighted in red

Obs.	INDUSTRIAL_PRODUCTION	INFLATION	OIL_PRICE	REAL_INTEREST_RATE	RISK_PREMIUM	TERM_STRUCTURE	FEARS	C
2010M02	0.067679	0.008475	-0.025476	-0.030661	-0.000650	-0.000389	-0.000817	-0.010861
2010M03	0.108245	0.068832	0.096834	0.097033	0.101200	0.104160	0.101741	0.021929
2010M04	0.143111	-0.336352	0.047749	-0.110732	-0.033098	-0.039062	-0.034619	-0.163068
2010M05	0.169528	0.167978	-0.106375	0.049483	-0.245364	-0.239380	-0.244299	-0.061704
2010M06	0.091555	-0.184323	0.054609	-0.097464	-0.027647	-0.032409	-0.030032	-0.094706

2010M07	0.073555	-0.080032	-0.067060	-0.168272	-0.157662	-0.155933	-0.156153	0.037650
2010M08	0.065082	0.018530	-0.057862	-0.213063	-0.140689	-0.160129	-0.141210	-0.218356
2010M09	0.059360	0.018401	-0.018144	0.032286	0.017033	0.016231	0.017293	-0.003516
2010M10	0.049720	0.057982	0.005839	0.117535	0.064331	0.057427	0.064078	0.052416
2010M11	0.067187	0.076327	-0.037887	0.092606	-0.275957	-0.285759	-0.276521	-0.081512
2010M12	0.077403	-0.007943	-0.010297	-0.003663	-0.000501	-0.000369	-0.000531	0.002256
2011M01	0.233043	-0.391294	0.236954	0.004999	0.095149	0.086847	0.094803	0.298662
2011M02	0.098425	-0.035097	-0.038832	-0.001942	0.012924	0.011962	0.013363	0.029876
2011M03	0.095616	-0.080784	-0.063877	0.012884	0.043331	0.045104	0.043003	-0.045923
2011M04	0.112616	0.313947	-0.134392	-0.111654	-0.061337	-0.051422	-0.061440	-0.076005
2011M05	0.023941	0.026266	0.046612	0.062817	-0.001688	-0.003167	-0.001341	-0.015872
2011M06	0.040933	-0.006451	-0.028298	-0.050633	-0.132921	-0.134222	-0.133106	-0.091213
2011M07	0.074360	-0.183860	0.013435	0.024135	0.079533	0.067557	0.078860	-0.034322
2011M08	0.153630	0.043774	0.185153	0.078346	1.486828	1.477655	1.478872	-0.184970
2011M09	0.133978	0.083988	-0.014010	-0.006971	-0.156443	-0.151337	-0.154559	0.072807
2011M10	0.202034	0.022519	0.004333	0.006332	-0.082608	-0.083587	-0.082487	0.061803
2011M11	0.153321	-0.153169	-0.051791	-0.291011	-0.911500	-0.952948	-0.910949	-0.130210
2011M12	0.249054	0.190214	-0.076227	0.057279	-0.308631	-0.335720	-0.321340	-0.427997
2012M01	0.149166	-0.003702	0.003526	0.003703	-0.011738	-0.011969	-0.011737	-0.002205
2012M02	0.106091	-0.000430	-0.017620	0.008047	-0.011837	-0.012116	-0.011755	0.003249
2012M03	0.105031	0.023634	0.019958	-0.016485	0.005686	0.006009	0.005854	0.023203
2012M04	0.072664	-0.017067	0.096815	0.115331	0.049905	0.047754	0.050689	0.041389
2012M05	0.118522	0.041019	0.065401	0.119253	0.111977	0.094214	0.108996	-0.107310
2012M06	0.145179	-0.043221	-0.023078	-0.001873	0.041826	0.036666	0.042415	0.024719
2012M07	0.096535	-0.065494	0.077643	-0.072903	-0.016300	-0.007181	-0.018350	-0.128974
2012M08	0.048557	-0.001523	-0.002857	0.004143	-0.001686	-0.001659	-0.001667	0.000999
2012M09	0.044272	0.021701	-0.013514	-0.038331	0.039532	0.037263	0.039679	0.040293
2012M10	0.047663	0.040218	0.043657	0.084741	-0.034721	-0.035128	-0.034379	0.096592
2012M11	0.040413	0.002901	-2.03E-05	0.003808	-0.001641	-0.001633	-0.001536	0.001703
2012M12	0.057289	-0.029761	0.017870	-0.010068	0.020900	0.021003	0.020913	0.008013
2013M01	0.150373	0.132711	-0.228188	-0.063751	-0.032417	-0.044491	-0.031567	0.005798
2013M02	0.228499	0.066008	-0.078464	0.043741	-0.008680	-0.007391	-0.005684	0.005164
2013M03	0.161852	-0.030328	0.035974	-0.012902	-0.007305	-0.003425	-0.005546	-0.003702
2013M04	0.138910	0.000710	0.011286	0.002713	-0.009775	-0.009617	-0.009782	-0.011751
2013M05	0.272240	-0.425595	0.187779	-0.115078	-0.274542	-0.290123	-0.259078	-0.515975
2013M06	0.290522	0.064801	-0.003733	0.051823	0.049017	0.060658	0.053430	0.021781
2013M07	0.133594	-0.097755	0.134109	-0.068924	0.100190	0.094005	0.096412	0.094823
2013M08	0.164700	0.138692	0.064041	0.156676	0.135783	0.138881	0.135935	0.317477
2013M09	0.045395	0.050744	-0.093713	-0.170064	-0.030799	-0.028842	-0.033693	-0.084223
2013M10	0.089343	-0.071232	-0.111006	-0.063996	0.180684	0.179344	0.181733	0.201903
2013M11	0.035224	-0.068648	0.031887	-0.039112	0.052352	0.049584	0.054190	0.088810
2013M12	0.061945	-0.017091	0.046420	-0.015903	0.025856	0.018878	0.025137	0.051989
2014M01	0.115125	-0.003642	0.198093	0.056581	-0.040203	-0.043682	-0.040369	-0.094669
2014M02	0.060169	-0.029673	0.110987	-0.009073	0.074862	0.075052	0.076228	0.098679
2014M03	0.127240	0.220669	-0.086236	0.103933	0.075405	0.075740	0.079009	0.271736
2014M04	0.092938	0.049217	0.050756	0.053725	0.026677	0.025082	0.027643	0.102631
2014M05	0.056633	-0.078892	-0.099901	-0.088584	0.071789	0.071971	0.073049	0.173593
2014M06	0.068422	0.052418	-0.033113	0.077784	0.058413	0.053407	0.058510	0.125042
2014M07	0.058506	0.045275	-0.040471	0.057529	0.063595	0.058422	0.060621	0.004574
2014M08	0.060085	-0.000802	-0.000886	-0.001702	0.000853	0.001217	0.000827	0.001972
2014M09	0.034293	-0.016898	-0.041725	-0.034587	-0.046309	-0.051948	-0.046200	0.016599
2014M10	0.094343	0.055024	0.064833	0.020012	0.014464	0.015315	0.016980	0.033957
2014M11	0.049701	0.036712	-0.025951	0.181924	0.092768	0.106117	0.093856	0.157207
2014M12	0.213320	0.242185	-0.039007	-0.242741	0.099522	0.084015	0.098855	0.221802
2015M01	0.454400	-0.245504	-0.851431	0.823939	0.058141	0.130872	0.052811	-0.259298
2015M02	0.243811	-0.012575	0.094961	0.092054	0.025651	0.024510	0.025154	-0.005926
2015M03	0.276523	0.124149	0.213749	0.359616	-0.068231	-0.027527	-0.067413	0.053709
2015M04	0.336572	0.062005	0.039121	-0.526700	-0.236097	-0.131426	-0.236850	-0.356157
2015M05	0.102698	0.027455	-0.008269	-0.080512	-0.001513	0.008642	-0.001323	0.014310
2015M06	0.207867	0.020683	0.022399	-0.067505	0.017938	0.030861	0.017722	-0.025956

Note: Outliers are highlighted in red

The influence statistics indicate the presence of outliers.

1. RStudent: 3 outliers
2. DFFITS: 6 outliers
3. COVRATIO: 8 outliers
4. Hat Matrix: 26 outliers
5. DFBETAS
    - Intercept: 7 outliers
    - Inflation: 4 outliers
    - Industrial Production: 6 outliers
    - Real Interest Rate: 4 outliers
    - Risk Premium: 5 outliers
    - Term Structure: 5 outliers
    - Oil Price: 1 outlier
    - FEARS: 5 outliers

The results from the leverage plots and influence statistics indicate that model (2) contains explanatory power. Outliers do not appear to have had an impact on the model as variables that have few outliers were not necessarily found to be statistically significant.

7. Japan

Endogeneity tests were conducted on regression models (1) and (2) and all variables were found to be exogenous. The robustness checks on (2) can also be found in Table D1 above. The residual of (2) was found to be stationary, normally distributed and no ARCH effects were found to be present. The leverage plots and influence statistics (Figure D7 and Table D8 below) are consistent with the regression results as only the observation of FEARS plot closely to the fit line, whereas the observations of other variables are widely dispersed. Moreover, the presence of outliers does not appear to be an issue as the number of outliers for each variable is quite low. Finally, output (4) in Table C10 in Appendix C shows the result of a correlation analysis between FEARS and the Nikkei VIX. This relationship, although negative in direction, was found to be statistically insignificant. Thus, it can be said that the relationship found between FEARS and Nikkei returns is a true statistical relationship and it not caused by noise trading. Overall, (2) suffers from serially correlated residuals but not from redundant variables, the presence of outliers, or the effects of noise trading.

Leverage plots and influence statistics were completed for model (2) – a macroeconomic APT model with the FEARS variable included.

Figure D7: Leverage Plots - Japan

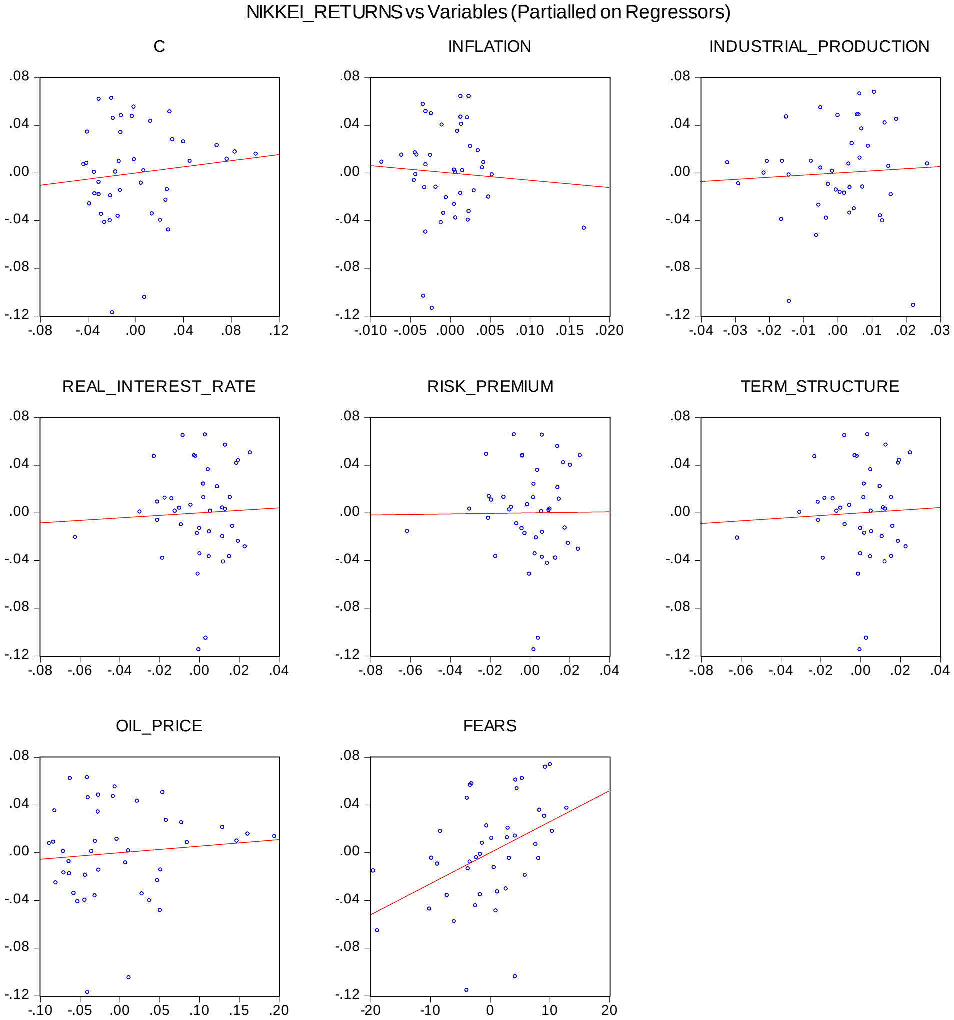

Table D8: Influence Statistics - Japan

Obs.	Resid.	RStudent	DFFITS	COVRATIO	Hat Matrix
2012M01	0.023819	0.554040	-0.127642	1.241685	0.050402
2012M02	0.047476	1.187402	-0.501683	1.070767	0.151471
2012M03	0.011208	0.261447	-0.067518	1.332200	0.062522
2012M04	-0.016517	-0.418824	0.212116	1.529193	0.204137
2012M05	-0.105454	-2.807019	0.987038	0.257293	0.110039
2012M06	0.003746	0.098112	-0.057804	1.706521	0.257674
2012M07	-0.051459	-1.229090	0.329020	0.951179	0.066868

2012M08	-0.026082	-0.632876	0.239148	1.317561	0.124949
2012M09	0.000815	0.019245	-0.005911	1.389425	0.086212
2012M10	0.035534	0.911211	-0.464702	1.311544	0.206401
2012M11	0.055387	1.358221	-0.468118	0.919345	0.106175
2012M12	0.041818	1.023317	-0.383174	1.127630	0.122967
2013M01	0.049626	1.197189	-0.370356	0.990142	0.087341
2013M02	0.039470	0.974855	-0.395781	1.178528	0.141504
2013M03	0.065058	1.601403	-0.517572	0.770633	0.094578
2013M04	0.047578	1.164637	-0.420986	1.040173	0.115564
2013M05	-0.021111	-0.657727	0.617804	2.153552	0.468731
2013M06	-0.003998	-0.099526	0.046369	1.541658	0.178346
2013M07	-0.014250	-0.445215	0.423803	2.307092	0.475376
2013M08	-0.031004	-0.749748	0.269868	1.252984	0.114700
2013M09	0.065652	1.621023	-0.536029	0.763122	0.098567
2013M10	-0.034426	-0.819282	0.246414	1.178611	0.082957
2013M11	0.048216	1.143500	-0.286636	0.988951	0.059119
2013M12	-0.013124	-0.319230	0.127169	1.435408	0.136958
2014M01	-0.114993	-3.309934	1.559286	0.156588	0.181622
2014M02	0.013312	0.328319	-0.143522	1.473451	0.160436
2014M03	-0.038251	-0.918802	0.297974	1.146539	0.095166
2014M04	-0.036106	-1.522464	2.290583	2.407513	0.693589
2014M05	-0.013195	-0.318709	0.120340	1.415551	0.124781
2014M06	0.012524	0.303428	-0.117493	1.427954	0.130388
2014M07	0.004906	0.114722	-0.031154	1.359053	0.068682
2014M08	-0.037418	-0.882109	0.227655	1.123962	0.062446
2014M09	0.002872	0.068143	-0.022179	1.402689	0.095789
2014M10	0.011167	0.268067	-0.096492	1.409532	0.114706
2014M11	-0.009103	-0.241885	0.150009	1.733371	0.277773
2014M12	0.020841	0.542805	-0.307433	1.561956	0.242874
2015M01	0.002710	0.081603	-0.072083	2.256890	0.438295
2015M02	0.014082	0.389410	-0.274058	1.830293	0.331240
2015M03	0.001638	0.042507	-0.024128	1.678114	0.243676
2015M04	0.006835	0.183598	-0.118391	1.783119	0.293695
2015M05	-0.017349	-0.722090	1.106984	3.752496	0.701508
2015M06	-0.042452	-1.049776	0.423164	1.134954	0.139777

Note: Outliers are highlighted in red

Obs.	C	INFLATION	INDUSTRIAL_ PRODUCTION	REAL_INTE REST_RATE	RISK_PREMI UM	TERM_STR UCTURE	OIL_PRICE	FEARS
2012M01	0.050402	0.076873	0.054400	0.028345	0.011061	0.010956	0.010387	0.074038
2012M02	0.151471	0.160752	0.105688	0.094735	0.308116	0.310170	0.301926	0.155122
2012M03	0.062522	-0.001183	0.042971	0.020809	0.039198	0.037903	0.039516	-0.002178
2012M04	0.204137	0.042773	-0.023196	-0.003942	-0.022320	-0.028362	-0.024483	0.045066
2012M05	0.110039	-0.097707	0.376192	0.500282	-0.091038	-0.121117	-0.083339	-0.077268
2012M06	0.257674	0.022634	-0.036976	-0.029094	-0.031740	-0.032704	-0.032447	0.021511
2012M07	0.066868	-0.152937	0.148672	0.093173	0.007877	0.001814	0.011269	-0.143989
2012M08	0.124949	-0.074910	-0.013348	0.044299	-0.124190	-0.124373	-0.120630	-0.071395
2012M09	0.086212	0.000606	0.000485	-0.003393	0.001055	0.001132	0.001014	0.000499
2012M10	0.206401	-0.055479	0.036230	0.085203	0.043404	0.036860	0.049516	-0.061543
2012M11	0.106175	-0.009023	-0.185132	-0.083789	0.175869	0.191385	0.172346	-0.018717
2012M12	0.122967	0.060375	0.058273	0.223150	0.201289	0.175442	0.200042	0.054032
2013M01	0.087341	-0.065784	-0.144972	-0.222817	-0.264847	-0.258712	-0.268490	-0.074036
2013M02	0.141504	-0.185664	-0.040715	0.172669	0.184453	0.203656	0.188475	-0.190602
2013M03	0.094578	-0.147386	0.083550	0.128652	0.047552	0.099716	0.056325	-0.152280
2013M04	0.115564	-0.016052	0.062248	0.083862	-0.020137	-0.042416	-0.019352	-0.022169
2013M05	0.468731	0.151341	0.016933	-0.166571	-0.098491	-0.028137	-0.091534	0.160973
2013M06	0.178346	0.014766	0.017935	0.037680	0.021498	0.021645	0.021702	0.015578
2013M07	0.475376	0.082099	0.074639	0.002964	0.357662	0.358895	0.355617	0.086422

2013M08	0.114700	0.099600	-0.070518	-0.045477	-0.171252	-0.184644	-0.170645	0.102312
2013M09	0.098567	-0.228194	0.151836	0.216423	-0.130260	-0.126273	-0.126430	-0.235520
2013M10	0.082957	0.055228	0.026814	-0.035660	-0.002053	-0.021186	-0.000487	0.059108
2013M11	0.059119	-0.096291	-0.105857	0.000746	-0.028022	-0.040305	-0.030406	-0.104081
2013M12	0.136958	0.051153	0.023289	-0.014649	-0.000437	0.012912	-0.000211	0.053706
2014M01	0.181622	0.308865	0.313280	-0.961922	0.008219	-0.071511	0.007349	0.328151
2014M02	0.160436	-0.063838	-0.033583	-0.087681	-0.046298	-0.044473	-0.046317	-0.066137
2014M03	0.095166	0.109255	-0.082284	-0.142558	-0.136443	-0.119073	-0.140931	0.113597
2014M04	0.693589	-0.167018	-1.749594	0.534263	0.474331	0.448238	0.481200	-0.171184
2014M05	0.124781	0.018890	-0.038786	-0.029583	-0.053228	-0.057124	-0.051776	0.020065
2014M06	0.130388	-0.061547	-0.051209	-0.062455	0.006751	0.005850	0.005268	-0.063815
2014M07	0.068682	-0.017963	-0.013718	-0.006929	-0.011043	-0.010450	-0.011084	-0.018682
2014M08	0.062446	0.085191	-0.024235	0.035723	-0.042384	-0.053970	-0.042667	0.088821
2014M09	0.095789	-0.005262	0.004206	0.012695	0.007831	0.006820	0.007746	-0.005632
2014M10	0.114706	-0.017114	-0.065490	-0.025968	-0.055972	-0.052154	-0.056739	-0.019349
2014M11	0.277773	-0.005801	0.048411	0.009375	0.024038	0.017985	0.020799	-0.004658
2014M12	0.242874	0.109228	0.083014	0.066328	0.052797	0.083446	0.057289	0.107986
2015M01	0.438295	0.047834	0.002210	0.033859	-0.012440	-0.010454	-0.012160	0.047193
2015M02	0.331240	0.141432	-0.078806	-0.181796	-0.076674	-0.092405	-0.079746	0.136949
2015M03	0.243676	0.016307	0.009720	-0.000873	0.005980	0.004477	0.005723	0.016009
2015M04	0.293695	0.079171	0.033375	0.008487	-0.008756	-0.002557	-0.011204	0.078194
2015M05	0.701508	-0.152508	-0.241324	-0.031223	0.012732	0.031874	-0.026111	-0.151731
2015M06	0.139777	-0.103138	0.048596	-0.175290	-0.128768	-0.094162	-0.130901	-0.094441

Note: Outliers are highlighted in red

The influence statistics indicate the presence of outliers.

1. RStudent: 2 outliers
2. DFFITS: 4 outliers
3. COVRATIO: 12 outliers
4. Hat Matrix: 15 outliers
5. DFBETAS
    - Intercept: 6 outliers
    - Inflation: 1 outliers
    - Industrial Production: 3 outliers
    - Real Interest Rate: 3 outliers
    - Risk Premium: 2 outliers
    - Term Structure: 3 outliers
    - Oil Price: 2 outliers
    - FEARS: 1 outliers

The results from the leverage plots and influence statistics indicate that model (2) lacks explanatory power. The number of outliers for each variable is low and hence this cannot be said to be the reason behind the result.

8. United Kingdom

Endogeneity tests were conducted on regression models (1) and (2) and all variables were found to be exogenous. The found to be exogenous. The robustness checks on (2) can also be found in Table D1 above. The residual of (2) was The residual of (2) was found to be stationary, normally distributed and no ARCH effects were found to be present. found to be present. The leverage plots and influence statistics (Figure D8 and

Table D9 below) are in alignment with the regression results and indicate that outliers are not an issue in this model. Finally, output (5) in Table C10 in Appendix C shows the result of a correlation analysis between FEARS and the FTSE VIX. This relationship was found to be positive and statistically significant at the 5% level of significance. This could indicate that the relationship found between FEARS and FTSE returns may not be a true one and is instead driven by noise (De Long, Shleifer, Summers, & Waldmann, 1990). Overall, (2) suffers from serially correlated residuals but not from redundant variables or the presence of outliers. Moreover, noise could be the driving force behind the relationship found.

Leverage plots and influence statistics were completed for model (2) – a macroeconomic APT model with the FEARS variable included.

Figure D8: Leverage Plots - United Kingdom

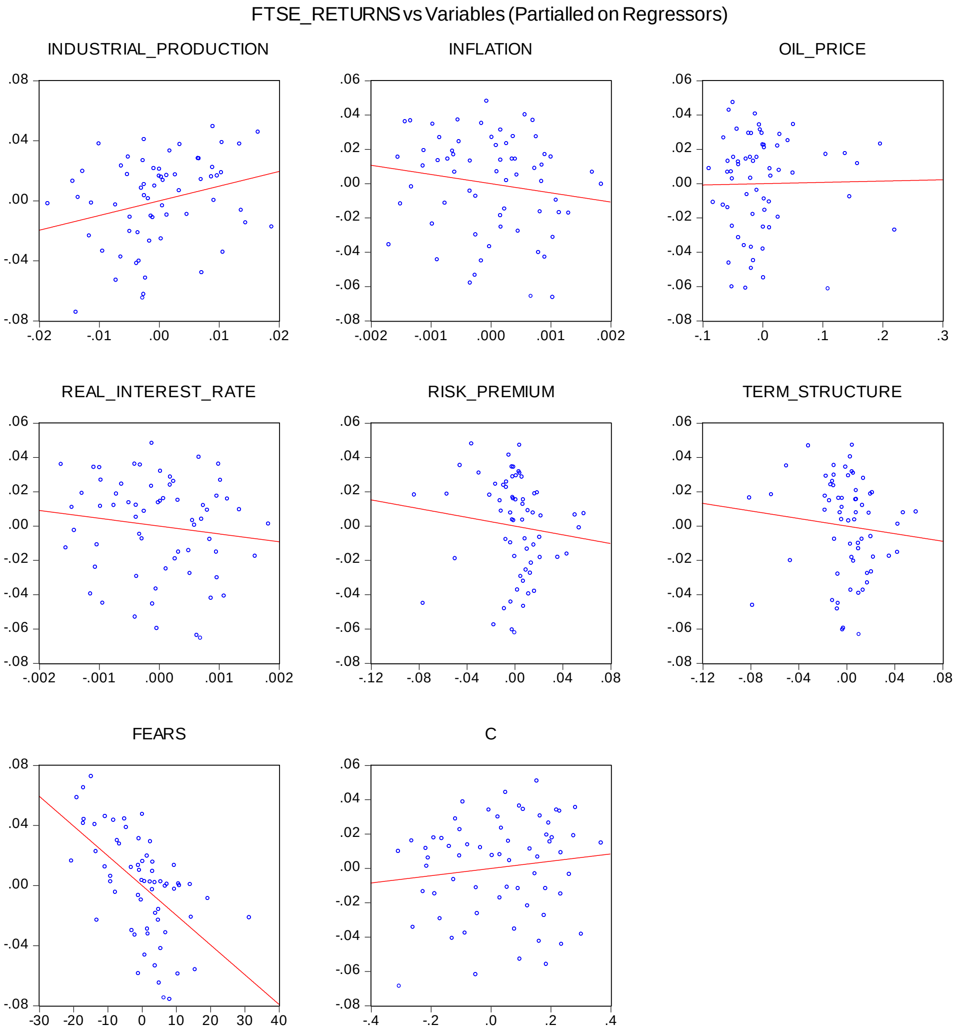

Table D9: Influence Statistics - United Kingdom

Obs.	Resid.	RStudent	DFFITS	COVRATIO	Hat Matrix
2010M03	0.024701	0.871841	-0.302538	1.159565	0.107475
2010M04	-0.010780	-0.377270	0.127304	1.260243	0.102222
2010M05	-0.038099	-1.324334	0.344495	0.959348	0.063378
2010M06	-0.025359	-0.910129	0.360645	1.185790	0.135711
2010M07	0.031347	1.113518	-0.393953	1.087336	0.111244
2010M08	0.005782	0.208062	-0.088166	1.353913	0.152229
2010M09	0.020927	0.742123	-0.272930	1.210816	0.119140
2010M10	0.021765	0.751503	-0.207118	1.145260	0.070596
2010M11	-0.025806	-0.883784	0.206221	1.088013	0.051636
2010M12	0.007475	0.305010	-0.219026	1.727158	0.340220
2011M01	0.040666	1.591541	-0.921336	1.075693	0.251004
2011M02	-0.003897	-0.135942	0.044924	1.277758	0.098456
2011M03	-0.035912	-1.327745	0.605095	1.083785	0.171974
2011M04	0.015659	0.567964	-0.249203	1.314464	0.161436
2011M05	0.009502	0.336024	-0.124848	1.293115	0.121301
2011M06	-0.010261	-0.360095	0.124868	1.269798	0.107339
2011M07	0.007260	0.258884	-0.102906	1.324591	0.136445
2011M08	-0.060805	-2.216372	0.742212	0.647942	0.100835
2011M09	-0.054902	-2.113252	1.055484	0.772834	0.199654

2011M10	0.043216	1.550191	-0.546087	0.922199	0.110395
2011M11	0.012854	0.450986	-0.155045	1.253992	0.105699
2011M12	0.011320	0.406310	-0.168119	1.320757	0.146179
2012M01	0.007076	0.254819	-0.108444	1.351432	0.153340
2012M02	0.014588	0.523837	-0.215922	1.298558	0.145228
2012M03	-0.013654	-0.473563	0.143874	1.221258	0.084502
2012M04	-0.012105	-0.421837	0.135816	1.242269	0.093925
2012M05	-0.045930	-1.705117	0.750189	0.913014	0.162176
2012M06	0.027093	1.000161	-0.469554	1.220353	0.180603
2012M07	0.008598	0.300603	-0.100921	1.268476	0.101296
2012M08	-0.019823	-0.709253	0.280713	1.242142	0.135432
2012M09	0.029335	1.066770	-0.454288	1.158319	0.153512
2012M10	-0.015638	-0.548412	0.186197	1.233210	0.103359
2012M11	-0.008969	-0.313835	0.106151	1.268906	0.102660
2012M12	0.004232	0.148509	-0.051900	1.291976	0.108841
2013M01	0.013497	0.498103	-0.242148	1.377527	0.191156
2013M02	0.028463	1.040444	-0.459229	1.180822	0.163050
2013M03	0.015452	0.526874	-0.123254	1.170174	0.051886
2013M04	0.032094	1.117691	-0.318678	1.043555	0.075182
2013M05	-0.024473	-0.893942	0.398953	1.234143	0.166090
2013M06	-0.059856	-2.225954	0.881458	0.670147	0.135553
2013M07	0.029506	1.073514	-0.458187	1.156736	0.154096
2013M08	-0.031201	-1.094952	0.344467	1.068234	0.090057
2013M09	0.013195	0.455349	-0.130195	1.212432	0.075574
2013M10	0.047642	1.659128	-0.382294	0.822986	0.050416
2013M11	-0.006303	-0.213486	0.045449	1.199430	0.043357
2013M12	0.022318	0.774043	-0.225650	1.149166	0.078328
2014M01	-0.044758	-1.658389	0.727034	0.932008	0.161210
2014M02	0.034280	1.175788	-0.253268	0.990941	0.044341
2014M03	-0.037010	-1.256272	0.183252	0.940706	0.020835
2014M04	0.029404	0.998243	-0.179113	1.032712	0.031190
2014M05	0.003322	0.112113	-0.021899	1.196936	0.036753
2014M06	-0.049281	-1.745807	0.506652	0.813456	0.077680
2014M07	0.003136	0.107314	-0.027892	1.231017	0.063277
2014M08	0.022599	0.769868	-0.166689	1.109836	0.044780
2014M09	-0.017837	-0.603360	0.115119	1.135561	0.035125
2014M10	0.015352	0.537253	-0.178907	1.230518	0.099821
2014M11	0.034129	1.194032	-0.353884	1.023888	0.080747
2014M12	0.016249	0.606860	-0.311411	1.383346	0.208437
2015M01	0.010448	0.445249	-0.358999	1.851880	0.393977
2015M02	0.021580	0.866125	-0.580411	1.501836	0.309900
2015M03	-0.028838	-1.107859	0.623081	1.274333	0.240303
2015M04	0.016398	0.589549	-0.243947	1.286334	0.146188
2015M05	-0.008773	-0.307872	0.107080	1.277068	0.107915
2015M06	-0.062192	-2.317923	0.909173	0.632302	0.133336

Note: Outliers are highlighted in red

Obs.	INDUSTRIAL_PRODUCTION	INFLATION	OIL_PRICE	REAL_INTEREST_RATE	RISK_PREMIUM	TERM_STRUCTURE	FEARS	C
2010M03	0.107475	0.192621	0.036340	0.076966	0.025752	-0.032403	-0.054381	-0.126852
2010M04	0.102222	-0.008071	-0.067769	-0.008595	-0.057833	-0.086166	-0.084228	-0.020008
2010M05	0.063378	0.079755	-0.184288	-0.001837	-0.180218	-0.078051	-0.068263	-0.183643
2010M06	0.135711	0.024373	-0.066565	-0.001957	-0.076485	0.242304	0.230803	-0.194467
2010M07	0.111244	0.032993	0.133414	-0.009628	0.184272	0.024948	0.033435	-0.257714
2010M08	0.152229	-0.008689	0.028556	0.022558	0.019155	0.060309	0.048278	-0.009117
2010M09	0.119140	0.000655	0.118452	0.004250	0.137030	0.065179	0.078919	-0.192272
2010M10	0.070596	0.079067	0.105034	0.038109	0.114156	0.073145	0.083429	0.031208
2010M11	0.051636	-0.004399	-0.140403	-0.020531	-0.133011	-0.058532	-0.078263	-0.018281

2010M12	0.340220	0.050915	0.005655	0.020361	-0.014295	-0.156640	-0.152302	-0.082289
2011M01	0.251004	0.256430	0.192382	-0.046105	0.278215	-0.045485	0.027295	0.736662
2011M02	0.098456	-0.001198	-0.023320	0.002730	-0.018366	-0.014677	-0.014350	0.024531
2011M03	0.171974	-0.427306	-0.173228	0.089539	-0.240272	-0.118398	-0.099664	0.055670
2011M04	0.161436	0.012064	0.156863	-0.059561	0.126296	-0.003882	-0.011229	-0.057207
2011M05	0.121301	-0.063085	0.098696	-0.063670	0.099463	0.027241	0.033674	0.017344
2011M06	0.107339	0.006284	-0.073865	0.062636	-0.092857	0.006899	-0.006130	0.001274
2011M07	0.136445	0.030467	0.018089	-0.029025	0.029998	-0.015802	-0.025350	0.051195
2011M08	0.100835	0.504935	-0.359654	0.131384	-0.224024	0.024971	0.038975	0.032693
2011M09	0.199654	-0.260926	0.093180	-0.006069	0.143362	0.898877	0.929724	-0.152616
2011M10	0.110395	-0.064451	0.140278	-0.182760	0.166195	-0.295704	-0.261122	-0.311504
2011M11	0.105699	0.005060	0.052180	-0.038669	0.058378	0.119279	0.112368	0.041192
2011M12	0.146179	-0.020305	-0.022569	-0.035060	-0.033776	-0.123944	-0.138097	-0.005979
2012M01	0.153340	0.041759	-0.064112	-0.032225	-0.041179	-0.004973	-0.007638	0.008390
2012M02	0.145228	0.023788	0.013837	-0.031278	0.001854	0.162600	0.164207	-0.047544
2012M03	0.084502	-0.035858	-0.016849	0.057228	-0.024479	-0.087961	-0.087863	-0.030120
2012M04	0.093925	0.080313	-0.054385	0.057868	-0.033240	-0.022488	-0.021971	0.052021
2012M05	0.162176	0.208710	0.044439	0.208120	0.031252	-0.066869	0.066593	-0.091281
2012M06	0.180603	-0.247788	0.002629	-0.142667	0.040470	-0.164380	-0.095511	-0.117152
2012M07	0.101296	0.051326	-0.041801	0.007551	-0.036293	0.034341	0.012651	-0.002983
2012M08	0.135432	-0.162480	0.171497	-0.038886	0.180569	-0.051881	-0.022082	0.075731
2012M09	0.153512	-0.048803	-0.167743	-0.003076	-0.192148	0.033984	0.081440	0.285057
2012M10	0.103359	0.044133	0.066416	-0.003772	0.091224	-0.061043	-0.064402	0.067874
2012M11	0.102660	0.006937	0.065691	-0.001532	0.071406	-0.026148	-0.015969	0.045887
2012M12	0.108841	-0.017751	-0.026569	0.004168	-0.034797	0.005131	0.005198	0.001605
2013M01	0.191156	0.076937	-0.051246	-0.063459	-0.001086	0.018487	0.036155	-0.097272
2013M02	0.163050	0.185648	-0.242627	0.064249	-0.282476	-0.010034	-0.060272	0.204523
2013M03	0.051886	0.002933	-0.051641	-0.022050	-0.058679	0.002246	-0.018050	0.021150
2013M04	0.075182	-0.230808	0.028607	-0.098696	0.004365	0.019795	0.026763	0.140217
2013M05	0.166090	0.143602	-0.025008	0.098567	-0.017267	-0.045023	-0.100681	0.257898
2013M06	0.135553	0.095310	0.123409	0.244178	0.014178	0.209840	0.033372	-0.246790
2013M07	0.154096	0.300571	-0.233237	-0.054367	-0.176526	-0.265135	-0.292703	-0.068777
2013M08	0.090057	0.114246	0.043343	0.092076	0.065658	-0.040310	-0.098966	-0.080143
2013M09	0.075574	-0.018416	-0.079032	-0.014718	-0.092565	-0.028828	-0.034135	0.032953
2013M10	0.050416	-0.265457	-0.017973	-0.167068	-0.030782	0.034094	0.039497	0.002441
2013M11	0.043357	0.016497	0.011435	0.011278	0.010832	-0.009281	-0.013963	-0.013509
2013M12	0.078328	-0.011041	-0.102659	0.003939	-0.118972	-0.064209	-0.043870	0.110206
2014M01	0.161210	-0.300616	0.460763	0.055619	0.314612	0.028916	0.106762	-0.019491
2014M02	0.044341	-0.096581	-0.027688	-0.013780	-0.074342	-0.006225	-0.005496	-0.078787
2014M03	0.020835	0.066144	0.004636	0.047812	0.010139	-0.013526	-0.022048	0.032931
2014M04	0.031190	-0.099352	0.056197	-0.037852	0.029028	0.005231	0.007247	-0.011965
2014M05	0.036753	0.005955	-0.010315	-0.004602	-0.006669	-0.001122	-0.002492	-2.60E-05
2014M06	0.077680	0.064856	0.242896	0.068481	0.259596	0.078924	0.071430	0.306539
2014M07	0.063277	-0.003152	0.004289	-0.011151	0.009913	-0.000558	0.000887	0.004239
2014M08	0.044780	-0.064855	0.010373	0.000144	-0.015011	-0.036907	-0.052600	0.015081
2014M09	0.035125	0.033776	-0.014801	0.019667	-0.024788	0.000440	-0.012983	-0.054254
2014M10	0.099821	-0.119112	0.072167	-0.010940	0.063716	-0.059365	-0.051127	0.052877
2014M11	0.080747	0.067496	-0.102112	0.126605	-0.059839	-0.014501	-0.065987	0.039667
2014M12	0.208437	-0.197151	0.036180	0.142433	0.007568	0.024062	0.025622	0.082616
2015M01	0.393977	-0.006461	-0.061630	0.179465	-0.033500	0.031522	-0.010913	-0.123996
2015M02	0.309900	0.108448	-0.082341	0.406312	-0.099202	-0.036975	0.041713	0.145074
2015M03	0.240303	-0.286107	0.185779	-0.554619	0.205590	-0.031404	0.047215	-0.028376
2015M04	0.146188	0.000105	0.038862	0.174073	0.030419	-0.005567	0.026152	0.001330
2015M05	0.107915	-0.046355	0.012274	-0.093772	0.014062	0.012099	0.016678	0.004543
2015M06	0.133336	0.106820	-0.249702	-0.538592	-0.261315	0.001958	-0.127782	-0.202668

Note: Outliers are highlighted in red

The influence statistics indicate the presence of outliers.

1. RStudent: 4 outliers
2. DFFITS: 7 outliers
3. COVRATIO: 5 outliers
4. Hat Matrix: 31 outliers
5. DFBETAS
    - Intercept: 6 outliers
    - Inflation: 8 outliers
    - Industrial Production: 4 outliers
    - Real Interest Rate: 5 outliers
    - Risk Premium: 5 outliers
    - Term Structure: 3 outliers
    - Oil Price: 2 outliers
    - FEARS: 3 outliers

The results from the leverage plots and influence statistics indicate that model (2) has very little explanatory power. Outliers are not necessarily the cause of this as even variables with few outliers did not turn out to be statistically significant.

9. United States

Endogeneity tests were conducted on regression models (1) and (2) and all variables were found to be exogenous. The robustness checks on (2) can also be found in Table D1 above. The residual of (2) was found to be stationary, normally distributed and no ARCH effects were found to be present. The leverage plots and influence statistics (Figure D9 and Table D10 below) are consistent with the regression results and indicate that outlier could be a reason behind the poor explanatory power of the model, as the number of outliers observed in this model is relatively higher than those observed in other countries' models. Finally, output (6) in Table C10 in Appendix C shows the result of correlation analysis between FEARS and the S&P500 VIX. This relationship was found to be positive and statistically significant at the 5% level of significance. This could indicate that the relationship found between FEARS and S&P500 returns is as a result of noise trading (De Long, Shleifer, Summers, & Waldmann, 1990) and not necessarily indicative of a true statistical relationship. Overall, (2) suffers from serially correlated residuals, a redundant variable and to a lesser degree the presence of outliers. Moreover, noise trading could be the driving force behind the relationship found.

Leverage plots and influence statistics were completed for model (2) – a macroeconomic APT model with the FEARS variable included.

Figure D9: Leverage Plots - United States

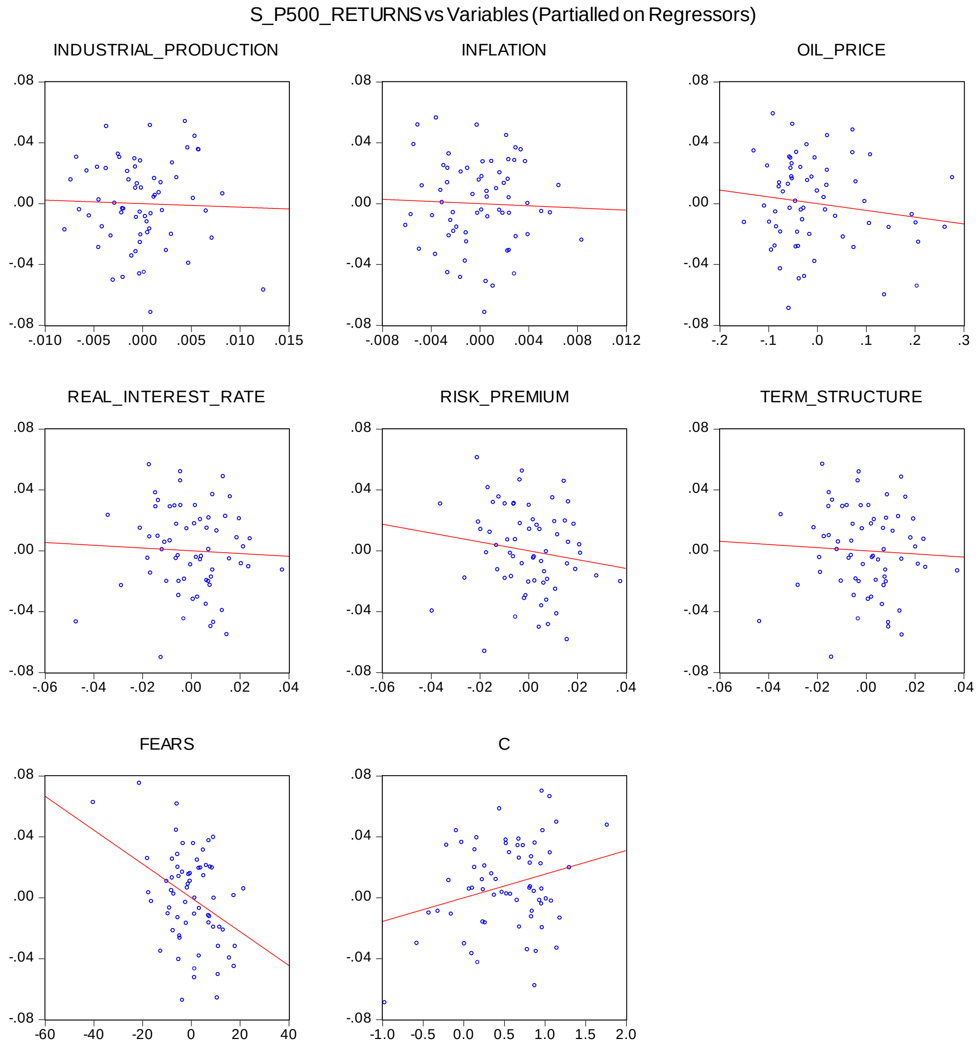

Table D10: Influence Statistics - United States

Obs.	Resid.	RStudent	DFFITS	COVRATIO	Hat Matrix
2010M02	0.005701	0.206539	-0.089074	1.358101	0.156826
2010M03	0.036624	1.294066	-0.401583	0.997820	0.087843
2010M04	0.004479	0.156488	-0.050274	1.266583	0.093554
2010M05	-0.053877	-2.134767	1.194200	0.808935	0.238347
2010M06	-0.025585	-0.941123	0.425646	1.224049	0.169816
2010M07	0.017788	0.696426	-0.426101	1.477849	0.272383
2010M08	-0.008432	-0.302056	0.120345	1.317723	0.136993
2010M09	0.051521	1.867455	-0.642855	0.794760	0.105947
2010M10	0.022792	0.789051	-0.211698	1.130493	0.067148

2010M11	-0.006694	-0.233583	0.073889	1.257559	0.090961
2010M12	0.008283	0.304237	-0.142085	1.384979	0.179056
2011M01	0.029792	1.056113	-0.357031	1.096405	0.102564
2011M02	0.013928	0.490294	-0.166923	1.242343	0.103870
2011M03	-0.021074	-0.779775	0.369759	1.294366	0.183575
2011M04	0.028834	1.047438	-0.432489	1.154653	0.145655
2011M05	-0.020647	-0.741937	0.293434	1.232038	0.135261
2011M06	-0.034717	-1.203067	0.291324	0.994454	0.055389
2011M07	-0.006481	-0.228705	0.080872	1.286524	0.111140
2011M08	-0.030354	-1.088568	0.405808	1.109830	0.122016
2011M09	-0.051078	-2.259715	1.782261	0.929776	0.383502
2011M10	0.054997	2.032072	-0.786619	0.749806	0.130320
2011M11	-0.009359	-0.340393	0.149906	1.352999	0.162440
2011M12	0.007489	0.259226	-0.074299	1.234855	0.075915
2012M01	0.037667	1.320972	-0.370486	0.972233	0.072924
2012M02	0.010227	0.353841	-0.100121	1.222320	0.074129
2012M03	-0.019043	-0.726998	0.401964	1.395416	0.234132
2012M04	0.004604	0.161395	-0.053774	1.275256	0.099919
2012M05	-0.022065	-0.794207	0.316246	1.220384	0.136856
2012M06	-0.000422	-0.014565	0.004110	1.243821	0.073760
2012M07	0.023849	0.827378	-0.227049	1.124121	0.070032
2012M08	-0.005577	-0.196836	0.069821	1.289917	0.111761
2012M09	0.020795	0.724679	-0.215001	1.163328	0.080901
2012M10	-0.046229	-1.609564	0.351886	0.840710	0.045615
2012M11	-0.016592	-0.586856	0.207062	1.233527	0.110708
2012M12	-0.031800	-1.114101	0.326585	1.049855	0.079130
2013M01	0.015330	0.525747	-0.127134	1.172379	0.055244
2013M02	0.014211	0.499071	-0.165865	1.234743	0.099468
2013M03	0.028002	0.959903	-0.204729	1.057092	0.043510
2013M04	0.022211	0.772430	-0.221496	1.145490	0.075979
2013M05	-0.049112	-1.831488	0.791184	0.858397	0.157267
2013M06	-0.071412	-2.698943	1.020840	0.495110	0.125158
2013M07	0.020122	0.740844	-0.342737	1.293710	0.176295
2013M08	-0.038194	-1.364479	0.466817	0.990683	0.104783
2013M09	0.027462	0.946918	-0.228619	1.073767	0.055080
2013M10	0.049883	1.813493	-0.651278	0.823956	0.114240
2013M11	0.009988	0.351004	-0.118725	1.261548	0.102663
2013M12	-0.018994	-0.660046	0.190859	1.173395	0.077162
2014M01	-0.029923	-1.051265	0.323409	1.078619	0.086459
2014M02	0.045462	1.613954	-0.481833	0.872186	0.081834
2014M03	-0.003404	-0.120105	0.042520	1.293843	0.111375
2014M04	-0.005735	-0.193907	0.035309	1.183940	0.032094
2014M05	0.016827	0.573983	-0.123290	1.150015	0.044103
2014M06	-0.004247	-0.143729	0.027106	1.189572	0.034344
2014M07	-0.011941	-0.413644	0.118321	1.216329	0.075634
2014M08	0.031770	1.099828	-0.271364	1.030176	0.057384
2014M09	-0.019573	-0.680256	0.196432	1.168651	0.076966
2014M10	0.012850	0.445870	-0.129931	1.215011	0.078273
2014M11	0.036859	1.353922	-0.576821	1.052018	0.153624
2014M12	-0.009239	-0.335491	0.146237	1.349165	0.159663
2015M01	-0.016199	-0.718165	0.626645	1.885784	0.432259
2015M02	0.029282	1.160133	-0.721006	1.320745	0.278626
2015M03	-0.004031	-0.152464	0.082558	1.484994	0.226735
2015M04	-0.003829	-0.136616	0.053088	1.322552	0.131191
2015M05	0.001406	0.050293	-0.019886	1.331766	0.135212
2015M06	-0.045172	-1.636293	0.595594	0.897971	0.116989

Note: Outliers are highlighted in red

Obs.	INDUSTRIAL_PRODUCTION	INFLATION	OIL_PRICE	REAL_INTEREST_RATE	RISK_PREMIUM	TERM_STRUCTURE	FEARS	C
2010M02	0.156826	0.009360	-0.005199	0.028457	-0.016628	-0.010458	-0.011266	-0.048135
2010M03	0.087843	0.248848	0.183082	0.127163	-0.168737	-0.193486	-0.173974	0.015354
2010M04	0.093554	0.006152	0.003857	0.002847	0.029984	0.030024	0.028345	-0.015160
2010M05	0.238347	-0.963931	-0.106149	-0.437080	-0.304273	-0.330755	-0.305530	-0.310104
2010M06	0.169816	0.007821	0.045227	-0.100014	0.251122	0.232047	0.244677	-0.216025
2010M07	0.272383	0.090930	0.005780	0.083666	0.009156	0.023944	0.015504	-0.390578
2010M08	0.136993	-0.002926	-0.008511	-0.045016	-0.064991	-0.077997	-0.067410	-0.028077
2010M09	0.105947	0.050499	-0.018901	0.186248	-0.072805	-0.043781	-0.047689	-0.499616
2010M10	0.067148	-0.119923	-0.033292	0.021662	0.136982	0.130492	0.134684	0.031267
2010M11	0.090961	0.016566	0.021532	-0.011841	-0.042686	-0.040596	-0.044430	-0.038278
2010M12	0.179056	0.087658	0.007774	2.53E-05	-0.038934	-0.056501	-0.043198	-0.020163
2011M01	0.102564	-0.082672	0.105485	-0.006737	0.016028	0.001844	0.010195	0.286029
2011M02	0.103870	-0.120596	0.041530	-0.034456	0.046195	0.052826	0.048735	-0.033577
2011M03	0.183575	-0.195106	-0.289578	0.017566	0.073473	0.071772	0.075228	0.097529
2011M04	0.145655	-0.243136	0.170005	-0.191026	-0.064586	-0.058936	-0.075096	0.106106
2011M05	0.135261	0.004459	-0.094901	0.041943	0.034227	9.34E-05	0.019535	0.154700
2011M06	0.055389	0.043557	0.180270	0.150981	-0.064937	-0.056534	-0.069675	-0.048139
2011M07	0.111140	-0.006695	0.001811	0.034083	0.036655	0.035965	0.039331	-0.033526
2011M08	0.122016	-0.090052	-0.106826	0.065799	-0.025077	-0.073326	-0.022575	0.065694
2011M09	0.383502	0.274461	-0.057286	0.138170	1.153908	0.978172	1.065592	-0.043707
2011M10	0.130320	0.303070	-0.313056	-0.254496	-0.317921	-0.394648	-0.330239	-0.151578
2011M11	0.162440	0.064478	0.058009	0.041348	-0.118149	-0.120524	-0.118324	-0.005846
2011M12	0.075915	0.014475	-0.034581	-0.027330	-0.039088	-0.036727	-0.039387	-0.003959
2012M01	0.072924	0.201866	0.162259	-0.038292	0.102190	0.116663	0.101721	-0.098567
2012M02	0.074129	-0.001323	0.020192	-0.036907	0.058627	0.051480	0.057034	-0.002096
2012M03	0.234132	0.209982	-0.131389	0.161051	-0.044825	-0.018304	-0.029208	0.053694
2012M04	0.099919	0.028116	0.016324	-0.015399	-0.015722	-0.012464	-0.016519	-0.003361
2012M05	0.136856	0.087471	0.086691	0.083151	-0.055752	-0.080805	-0.052958	-0.159673
2012M06	0.073760	0.001372	0.001879	0.000879	0.001533	0.001713	0.001532	0.001809
2012M07	0.070032	-0.019266	-0.101440	-0.057591	0.102311	0.110358	0.096878	0.039550
2012M08	0.111761	0.042819	-0.020283	0.015176	-0.006810	-0.009411	-0.009063	0.017812
2012M09	0.080901	-0.036552	0.049349	-0.053132	0.024644	0.012316	0.021752	0.157434
2012M10	0.045615	0.015114	0.174580	0.161888	-0.127999	-0.114373	-0.128863	0.100565
2012M11	0.110708	-0.014591	0.151869	0.079069	-0.043432	-0.041371	-0.040619	0.065804
2012M12	0.079130	0.025250	0.231176	0.130416	-0.007897	0.017013	-0.008409	0.064478
2013M01	0.055244	-0.024025	-0.001475	-0.036846	0.029763	0.021202	0.032590	-0.003045
2013M02	0.099468	0.031659	0.136811	-0.013622	-0.007864	0.001709	-0.007336	-0.006419
2013M03	0.043510	-0.006359	0.038253	-0.072402	-0.071891	-0.081253	-0.080169	0.072607
2013M04	0.075979	-0.095024	-0.084551	-0.035387	0.049265	0.073973	0.056931	-0.053619
2013M05	0.157267	0.126681	0.126694	0.067262	-0.137344	-0.074560	-0.157004	0.296944
2013M06	0.125158	-0.079198	-0.046035	0.217844	0.302532	0.446517	0.348029	0.123707
2013M07	0.176295	-0.147428	-0.050442	-0.107674	-0.236498	-0.253225	-0.241804	0.049966
2013M08	0.104783	-0.216456	0.069316	0.009589	-0.156525	-0.142327	-0.170067	-0.189579
2013M09	0.055080	0.094699	0.009839	-0.068748	-0.120546	-0.121119	-0.126502	0.028521
2013M10	0.114240	-0.226115	-0.393029	-0.126028	0.214719	0.240399	0.238723	0.210299
2013M11	0.102663	-0.008105	-0.070563	-0.028698	0.076247	0.066529	0.074416	0.041012
2013M12	0.077162	-0.011364	0.059115	0.074374	0.016230	0.041719	0.024507	0.016468
2014M01	0.086459	0.156640	-0.106196	0.055488	0.048047	0.010259	0.045881	0.098203
2014M02	0.081834	0.287465	0.148348	0.045206	-0.062923	-0.052367	-0.047940	0.144407
2014M03	0.111375	-0.026377	-0.025908	-0.002727	-0.004460	-0.002489	-0.003216	-0.005020
2014M04	0.032094	0.001574	-0.014856	0.008477	0.010497	0.010567	0.011629	0.005478
2014M05	0.044103	0.022937	0.054708	-0.008263	-0.029764	-0.017240	-0.026715	-0.053694
2014M06	0.034344	-0.009467	-0.000845	0.005243	-0.002576	-0.002554	-0.003070	0.014024
2014M07	0.075634	-0.006334	0.041259	0.016972	-0.032158	-0.024080	-0.029205	-0.092317
2014M08	0.057384	-0.089557	-0.114763	-0.062282	-0.129936	-0.118970	-0.132750	-0.045356
2014M09	0.076966	-0.066379	0.032104	-0.048678	-0.042768	-0.037759	-0.049456	-0.093729
2014M10	0.078273	-0.008048	-0.049598	0.011677	-0.082705	-0.082186	-0.084510	-0.019592
2014M11	0.153624	0.267854	-0.319457	0.208191	0.200465	0.206095	0.203612	0.087420

2014M12	0.159663	0.007180	0.082868	-0.069834	0.000780	0.008308	0.003514	-0.039890
2015M01	0.432259	0.125025	0.072470	-0.256610	0.135196	0.103897	0.151091	0.198331
2015M02	0.278626	-0.034619	0.156954	0.491251	-0.049763	-0.070108	-0.024372	0.140191
2015M03	0.226735	0.010722	-0.040218	-0.058850	-0.023118	-0.023723	-0.021590	-0.015473
2015M04	0.131191	0.009461	-0.009515	-0.038433	0.006684	0.009386	0.007573	-0.012323
2015M05	0.135212	-0.007658	0.008524	0.013621	0.003295	0.003402	0.003416	0.000953
2015M06	0.116989	-0.009531	-0.197579	-0.461766	0.045405	0.079939	0.048224	-0.029550

Note: Outliers are highlighted in red

The influence statistics indicate the presence of outliers.

1. RStudent: 4 outliers
2. DFFITS: 6 outliers
3. COVRATIO: 6 outliers
4. Hat Matrix: 30 outliers
5. DFBETAS
    - Intercept: 5 outliers
    - Inflation: 6 outliers
    - Industrial Production: 4 outliers
    - Real Interest Rate: 5 outliers
    - Risk Premium: 5 outliers
    - Term Structure: 5 outliers
    - Oil Price: 4 outliers
    - FEARS: 4 outliers

The results from the leverage plots and influence statistics indicate that model (2) lacks some explanatory power as only two variables are statistically significant. Although this model has more outliers than seen in other countries it does not seem to be reason for the model as even those variables with fewer outliers were not declared to be statistically significant.